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DUAL PERSPECTIVES ON BLENDED LEARNING EFFECTIVENESS: A HYBRID PLS-SEM AND FSQCA ANALYSIS OF MULTIDIMENSIONAL DETERMINANTS

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ABSTRACT

The growing integration of interactive technologies is reshaping higher education worldwide, offering more adaptive and flexible environments. Within this transformation, blended learning (BL), the strategic combination of face-to-face and online instruction, has become a pivotal approach to enhance learning outcomes in the digital era. This study aims to investigate the key determinants of BL effectiveness in Thai higher education from the dual perspectives of students and teachers. Data were collected from 242 respondents and analysed using a novel hybrid methodology that integrates partial least squares structural equation modelling (PLS-SEM) with fuzzy-set qualitative comparative analysis (fsQCA). The results indicate that course interaction and course design are the critical determinants influencing BL effectiveness across both groups, while technological and institutional factors exhibit role-specific priorities: students emphasize system quality and technical support, whereas instructors focus on information quality and policy support. These findings highlight the need for differentiated institutional strategies, suggesting that Thai higher education should enhance technological assistance and platform quality for students, while providing teachers with adequate resources and policy support to sustain high-quality course design. The fsQCA results further identify multiple sufficient configurations, demonstrating that individual factors, including computer self-efficacy and technology experience, contribute to BL effectiveness only when embedded within other supportive conditions. By combining symmetric and asymmetric approaches, this study provides comprehensive empirical evidence and innovative solutions to enhance the effectiveness of technology-enhanced learning in higher education in developing countries.

KEYWORDS: Blended Learning, Higher Education, Fuzzy-Set Qualitative Comparative Analysis, Multigroup Analysis, Digital Technology, Structural Equation Modelling.

1. INTRODUCTION

The incorporation of information and communication technology (ICT) within higher education has become crucial in enhancing the effectiveness of contemporary teaching and learning practices (Alsabawy et al., 2016). ICT expands the availability of learning resources while enabling novel pedagogical methods tailored to meet the varied demands of learners. Among these, blended learning (BL) has gained significant traction as a transformative instructional model, combining the strengths of face-to-face instruction with the flexibility and interactivity of e-learning (Imran et al., 2023). This hybrid approach aligns well with the demands of today's learners, offering substantial advantages in enhancing education accessibility, improving student engagement, and promoting personalised learning experiences (Inprasitha, 2023). Despite the growing utilisation of the BL model in higher education (Castro, 2019), ensuring and sustaining its effectiveness in practice remains a persistent challenge. Over the past decades, scholarly attention has gradually shifted from the initial adoption phase to investigating the post-adoption impact of BL initiatives. However, the majority of existing research predominantly adopts a single-stakeholder perspective, focusing primarily on either learners or instructors (Jiang, 2022). For instance, learner-centred studies (Dewi et al., 2018; Ghazal et al., 2018; McGuinness & Fulton, 2019; Thurber & Trautvetter, 2020) have examined how personal characteristics, course interaction, and content design features affect students' satisfaction and performance. Similarly, instructor-focused investigations (Müller et al., 2023; Zhang & Dang, 2020; Zhao & Song, 2021) have emphasised the importance of pedagogical components, institutional support, and technology infrastructure in facilitating the effectiveness of BL implementation. This unidimensional viewpoint neglects the interconnected contributions of both knowledge creators and receivers in shaping BL outcomes. While some studies (Alomari et al., 2020) have attempted to incorporate both perspectives, their scope remains constrained, as they often concentrate on a narrow range of variables (Ashraf et al., 2023) or do not perform comparative analysis, especially in developing countries (Min & Yu, 2023). In addition, most studies used quantitative methods to examine linear relationships (Liu & Yodmongkol, 2023); however, BL effectiveness is rarely driven by a single factor but rather by multiple and potentially substitutable configurations of conditions.

These gaps underscore the need to reconceptualise BL effectiveness as a co-constructed outcome shaped by the interplay between students and instructors. Such an approach requires moving beyond narrow viewpoints and linear relationships to capture the multidimensional influences of individual, institutional, technological, and instructional factors. To address these issues, this study applies a novel hybrid methodological design that combines symmetric partial least squares structural equation modelling (PLS-SEM) and asymmetric fuzzy-set qualitative comparative analysis (fsQCA) approaches. Specifically, PLS-SEM is employed to validate hypothesised relationships, complemented by multi-group analysis (MGA) to assess differences between groups. In parallel, fsQCA is used to identify configurations of conditions that are sufficient and necessary for an outcome to occur. Thailand, as an emerging educational hub in Southeast Asia, has made substantial policy-level investments to promote BL through its National Education Plan 2017-2036, offering a timely and relevant context for this empirical investigation. The integration of PLS-SEM and fsQCA in this research enabled a comprehensive examination that combined quantitative and qualitative perspectives. PLS-SEM provided insights into the significance and relationships of variables, while fsQCA extended the analysis by uncovering causal configurations and complex condition patterns. This hybrid approach and dual perspective facilitated a deeper and more holistic examination of the determinants influencing BL effectiveness in Thai higher education. This combination not only reinforced the study's validity and reliability but also provided comprehensive insights and evidence-based implications for higher education policymakers and practitioners in Thailand and other developing countries in Asia, enabling them to optimise their BL strategies and thereby enhance BL implementation, ultimately facilitating its sustainable development.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Blended Learning Effectiveness

The effectiveness refers to "the aptitude to fulfil the desired purpose," commonly measured as the ratio of results to objectives (Gulluscio, 2021). It reflects the extent to which learning objectives are achieved and desired outcomes are realised in the BL context (Dewi et al., 2018), encompassing dimensions such as satisfaction, performance, motivation, knowledge construction, and learning experience (Kintu et al., 2017; Min & Yu, 2023). Accordingly, BL effectiveness can be conceptualised as the perceived degree to which BL initiative facilitates learning or teaching goals, indicated by outcomes such as satisfaction, goal attainment, engagement, and performance. Based on a systematic literature review, eight determinants of BL effectiveness were identified, spanning individual, technological, institutional, and instructional dimensions. The proposed model, which integrates these determinants, is illustrated in Figure 1, with the research hypotheses detailed in the subsequent sections.

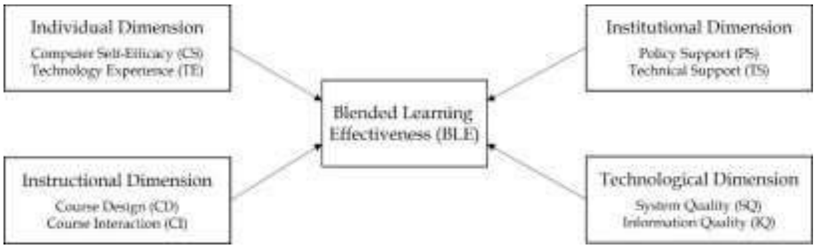

Figure 1: Research Model.

2.2. Individual Dimension

Computer self-efficacy (CS) is defined as an individual's belief in their ability to effectively use computers to complete educational tasks (Prifti, 2022). It has been widely acknowledged as a critical determinant of learner satisfaction and academic performance in technology-enhanced environments (Gunawardena et al., 2010; Wu et al., 2010). Empirical studies have confirmed that students with higher CS experience enhanced satisfaction (Katsarou, 2021) and improved learning outcomes (Zhou et al., 2023). For instructors, CS has also been found to influence their satisfaction positively (Du et al., 2023) and teaching performance (Hizam et al., 2021).

Technology experience (TE) refers to the familiarity, proficiency, and knowledge that an individual possesses with digital technologies. Studies show that students who are proficient in using online tools tend to participate more actively in collaborative learning and interactive tasks (Al-Samarraie & Saeed, 2018). Ultimately, they acquire higher learning competencies and outcomes (Majeed & Rehan Dar, 2022). Conversely, unfamiliarity with technology functionalities may hinder usage and reduce engagement (Suwantarathip & Wichadee, 2014). For instructors, low digital competence has been identified as a significant barrier to collaborative BL teaching (Schneckenberg et al., 2011). In contrast, higher TE enables teachers to design, manage, and deliver content more effectively, thereby improving learning outcomes (Ghazal et al., 2018). Therefore, the following is hypothesised:

H1: Computer self-efficacy has a positive influence on the effectiveness of blended learning.
H2: Technology experience has a positive influence on the effectiveness of blended learning.

2.3. Technological Dimension

System quality (SQ) refers to the degree to which a learning system is reliable, flexible, integrated, accessible, timely, and functionally complete in supporting user tasks (Li & Zhu, 2022). Empirical evidence has shown that technological limitations, such as browser incompatibility, unstable internet connectivity, and poor audio quality, can significantly disrupt learning experiences (McGuinness & Fulton, 2019). An easy-to-navigate system allows users to focus on learning rather than operation, enhancing satisfaction and academic performance (Chen & Yao, 2016). The ease and flexibility of e-learning platform access positively influence learner satisfaction (Katsarou, 2021), while system accessibility significantly affects both teachers' and students' engagement in BL environments (Zhou et al., 2023).

Information quality (IQ) refers to the relevance, timeliness, accuracy, completeness, sufficiency, consistency, accessibility, clarity, and proper formatting of content for target users (Roca et al., 2006). Both SQ and IQ were identified as fundamental predictors of students' satisfaction in digital learning contexts (Nikou & Maslov, 2023). When educational content is timely, explicit, and relevant, learners are more likely to perceive the system as applicable and to remain engaged throughout the course. McGuinness and Fulton (2019) further demonstrated that accessible and well-structured e-tutorials can enhance user engagement, while Majeed and Rehan Dar (2022) found a significant relationship between access to online learning resources and student performance. Similarly, Alomari et al. (2020) and Sanusi (2022) highlighted that the availability and visibility of resources positively affect users' satisfaction and experience in BL settings. Therefore, the following is hypothesised:

H3: System quality has a positive influence on the effectiveness of blended learning.

H4: Information quality has a positive influence on the effectiveness of blended learning.

2.4. Institutional Dimension

Policy support (PS) refers to the establishment of guidelines, frameworks, and regulations that govern the implementation and operation of BL programs at the administrative level. Empirical evidence (Anthony et al., 2019) has revealed that PS towards BL significantly influences the effectiveness of teaching and learning outcomes. Ibrahim and Nat (2019) further emphasised that successful BL implementation necessitates supportive policy frameworks, active leadership engagement, and institutional practices that support BL courses.

Technical support (TS) involves training and instruction, assistance and guidance, and troubleshooting services related to the use of technology for educators and learners engaged in BL activities. Zhang and Dang (2020) demonstrated that providing adequate TS significantly enhances the outcomes of BL initiatives, and TS is a key determinant of users' satisfaction and engagement (Taghizadeh & Hajhosseini, 2021). Faculty members anticipate comprehensive TS and professional development in technology, which positively influences their intention to adopt BL (Ibrahim & Nat, 2019). Learners similarly benefit from strong TS, as enhanced TS leads to greater engagement (Feng et al., 2023). Therefore, the following is hypothesised:

H5: Policy support has a positive influence on the effectiveness of blended learning.

H6: Technical support has a positive influence on the effectiveness of blended learning.

2.5. Instructional Dimension

Course interaction (CI) refers to the timely and supportive communication that occurs between teachers and students during the learning process. Effective CI has been proven to enhance learning effectiveness and engagement in the BL environment (Su et al., 2023). Prompt communication, instructor assistance, and responsiveness have a significant impact on learning experiences and outcomes (Levy & Ramim, 2017), as well as student satisfaction (Ho et al., 2022). Conversely, long delays lead to reduced satisfaction and engagement (Dwivedi et al., 2019). Consistent with this, prior studies also highlighted the importance of instructor feedback in fostering satisfaction, engagement, and learning effectiveness (M. Huang et al., 2022; Levy & Ramim, 2017).

Course design (CD) involves the strategic structuring of content, technology, and learning activities to foster high-quality and engaging learning environments. The quality of CD has been proven to positively impact students' satisfaction (Rima Aditya et al., 2019) and overall learning effectiveness (Müller et al., 2023). In the Thai university context, Kwak et al. (2015) further confirmed that well-structured CD has a direct influence on learners' motivation and academic achievement. Therefore, the following is hypothesised

H7: Course interaction has a positive influence on the effectiveness of blended learning.

H8: Course design has a positive influence on the effectiveness of blended learning.

3. METHODOLOGY

3.1. Data Collection and Participants

This study was conducted at a comprehensive public university in Thailand, purposefully selected for its accessibility, alignment, and long-standing engagement in BL practice. As a national leader in digital education, the university has integrated BL into its curriculum for over two decades. More than 1,300 BL courses are now offered, supported by digital platforms, physical facilities, faculty development programs, funding, and student-centred technology initiatives. Following established BL self-evaluation frameworks as stated by Lim and Wang (2016), it has achieved a mature level of BL integration, making it a suitable research context.

To examine the key determinants of BL effectiveness from the perspectives of teachers and students, stratified random sampling was employed to ensure representative participation from both groups. Data collection was conducted through online and face-to-face survey distribution methods. The ethical considerations were addressed by clearly outlining the study's purpose, the right to withdraw, and requiring informed consent at the start of the survey; only consenting participants could proceed. In total, the study received 128 valid responses from students and 114 valid responses from teachers. These participants were distributed across various faculties and represented diverse academic disciplines. This sample size satisfies the 1:10 ratio for PLS path modelling as recommended by Hair et al. (2017).

3.2. Measurement Instruments

The questionnaire was developed based on established and validated instruments from previous studies, with minor wording adjustments to align with the context of BL. The instrument consisted of 34 items, organised into two sections. The first section collected demographic details, including faculty affiliation, age, and gender. The second section focused on measuring key determinants using a five-point Likert scale. Each construct was measured using 3 to 4 items to ensure model fit and support the reliability and validity of the instrument.

To ensure the validity of the adapted items, content validity was reassessed through expert judgment. Following the methodology proposed by Mora et al. (2016), six BL experts were invited to evaluate the construct belonging and clarity of each item. The evaluation results were summarised in Table 1, which included the Aiken index (V), Lower Confidence Limit (LCL), Expected Accordance Proportion (EAP) and Average Accordance Proportion (AAP), with a Z-value of 1.645 corresponding to a 90% confidence interval. The minimum threshold for V is 0.7, and an item is considered valid only if its LCL also exceeds 0.7, as recommended by Soto and Segovia (2009). Items measuring TE fell below this threshold and were revised based on expert feedback to improve clarity and construct alignment.

Table 1: The Result of Content Validity through Expert Evaluation.

Construct	Construct Belongings				Clarity			
	V	LCL	EAP	AAP	V	LCL	EAP	AAP
Computer Self-efficacy (CS)	0.861	0.710	89%	89%	0.861	0.710	89%	89%
Technology Experience (TE)	0.792	0.631	78%	83%	0.792	0.630	89%	83%
System Quality (SQ)	0.948	0.819	100%	96%	0.948	0.819	100%	96%
Information Quality (IQ)	0.896	0.752	92%	92%	0.896	0.752	92%	92%
Policy Support (PS)	0.885	0.738	83%	91%	0.885	0.738	83%	91%
Technical Support (TS)	0.917	0.777	83%	93%	0.917	0.777	83%	93%
Course Interaction (CI)	0.907	0.766	98%	93%	0.907	0.766	98%	93%
Course Design (CD)	0.917	0.778	100%	93%	0.917	0.778	100%	93%
BL Effectiveness (BLE)	0.875	0.726	92%	90%	0.875	0.726	92%	90%

Following expert validation, the revised questionnaire was pre-tested with 18 participants to assess reliability and construct validity. The pre-test results indicated that all constructs achieved Cronbach's alpha values exceeding the 0.7 threshold, and within-construct item correlations were consistently higher than correlations between items of different constructs. These findings confirmed that the instrument possessed satisfactory internal consistency and construct validity and was therefore deemed appropriate for data collection.

3.3. Data Analysis Method

A hybrid research analysis approach, PLS-SEM-fsQCA, was employed in this study to investigate the symmetric and asymmetric relationships amongst the constructs in the integrated model. PLS-SEM, as a symmetrical method grounded in regression techniques, enables researchers to examine the strength and direction of the relationships between variables (Foroughi et al., 2024). While fsQCA is an asymmetrical approach method, integrating the empirical rigour and logical coherence of qualitative inquiry with the broad applicability and generalizability of quantitative analysis (Ragin, 2000), it allows for a sophisticated exploration of causal mechanisms (Ragin, 2009). This advanced approach is efficient for tackling complicated causal relationships, as it can handle the combinations of multiple conditions and configurational dependencies (Alkawsi et al., 2024). While fsQCA emphasises identifying causal configurations, PLS-SEM contributes predictive precision, together enhancing the comprehension of how antecedent conditions shape BL effectiveness (Alam et al., 2025). The joint application of fsQCA and PLS-SEM facilitates a rigorous and multifaceted exploration of the data, allowing the study to integrate quantitative evaluation with qualitative configurational analysis and thereby generate a more holistic understanding (Chanda et al., 2024).

The PLS-SEM typically comprises two components: the measurement model, which is responsible for testing the reliability and validity of latent constructs through observed measures (Hair et al., 2017), and the structural model, which examines the proposed relationships among latent variables (Dakduk et al., 2018). PLS-SEM offers notable benefits by accommodating deviations from normality, being appropriate for small sample sizes often found in country-specific research, and facilitating the modelling of complex relationships among multiple latent constructs (Alkawsi et al., 2024). SmartPLS 4.1 software was utilised in this study to conduct the PLS analysis, as it supports efficient tabulation, concise summarisation, and thorough analysis. The fsQCA analysis procedure involves three main steps: data calibration, necessary condition analysis (NCA), and truth table construction (Al-Emran et al., 2023). The fsQCA 4.0 software was employed in this study. All causal conditions in the analysis are operationalised through fuzzy set calibration, with values ranging continuously from 0 to 1, indicating full non-membership to complete membership, respectively (Shahzad et al., 2025). NCA was subsequently conducted to identify the necessary conditions for BL effectiveness.

A truth table was then created, and sufficient analysis was conducted to identify the core conditions, peripheral conditions, and sufficient configurations that lead to BL effectiveness.

4. RESULTS

4.1. Symmetric analysis result

4.1.1. Assessment of Measurement Model

To assess the measurement quality of the constructs, internal consistency reliability, convergent validity, and discriminant validity were examined. Internal consistency was evaluated using Cronbach's alpha (α) and composite reliability (CR). Convergent validity was assessed by examining item loadings (FL) and average variance extracted (AVE). As shown in Table 2, all constructs demonstrated Cronbach's α and CR values exceeding the recommended threshold of 0.70 (Hair et al., 2017), indicating satisfactory reliability.

All item loadings exceeded 0.70, and the AVE values for all constructs were above 0.50, meeting the widely accepted criteria for convergent validity (Fornell & Larcker, 1981).

Table 2: Constructs Measures and Loading Results.

Constructs	Indicators	Total sample = 242				Students = 128				Teachers = 114			
		FL	α	CR	AVE	FL	α	CR	AVE	FL	α	CR	AVE
Computer Self-Efficacy	CS1	0.911	0.833	0.899	0.748	0.918	0.783	0.873	0.697	0.915	0.878	0.924	0.802
	CS2	0.804				0.748				0.854			
	CS3	0.876				0.83				0.918			
Technology Experience	TE1	0.89	0.862	0.916	0.784	0.864	0.825	0.896	0.741	0.912	0.891	0.932	0.821
	TE2	0.891				0.857				0.918			
	TE3	0.876				0.861				0.889			
System Quality	SQ1	0.798	0.863	0.907	0.709	0.831	0.861	0.906	0.707	0.79	0.871	0.912	0.722
	SQ2	0.841				0.847				0.847			
	SQ3	0.858				0.812				0.896			
	SQ4	0.869				0.87				0.861			
Information Quality	IQ1	0.872	0.875	0.914	0.728	0.848	0.857	0.903	0.7	0.899	0.895	0.927	0.76
	IQ2	0.867				0.866				0.869			
	IQ3	0.861				0.849				0.884			
	IQ4	0.81				0.781				0.835			
Policy Support	PS1	0.878	0.903	0.932	0.774	0.863	0.887	0.922	0.747	0.899	0.917	0.942	0.801
	PS2	0.89				0.867				0.916			
	PS3	0.858				0.866				0.854			
	PS4	0.892				0.861				0.911			
Technical Support	TS1	0.882	0.883	0.928	0.81	0.847	0.858	0.913	0.779	0.912	0.906	0.94	0.84
	TS2	0.913				0.9				0.926			
	TS3	0.906				0.899				0.912			
Course Interaction	CI1	0.844	0.844	0.906	0.762	0.846	0.862	0.916	0.785	0.849	0.822	0.894	0.738
	CI2	0.898				0.897				0.899			
	CI3	0.876				0.914				0.828			
Course Design	CD1	0.862	0.872	0.921	0.796	0.879	0.856	0.913	0.777	0.845	0.883	0.928	0.813
	CD2	0.898				0.856				0.937			
	CD3	0.916				0.909				0.919			
BL Effectiveness	BLE1	0.898	0.911	0.937	0.789	0.859	0.893	0.926	0.757	0.936	0.927	0.949	0.822
	BLE2	0.918				0.882				0.951			
	BLE3	0.861				0.85				0.874			
	BLE4	0.875				0.889				0.863			

Discriminant validity is fundamental to empirical analyses of inter-construct relations (Henseler, 2020). It was evaluated using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceed its correlations with all other constructs (Fornell & Larcker, 1981).

As reported in Table 3, the square root of the AVE for each construct exceeded its corresponding inter-construct correlations, indicating that each construct within the model differs from the others.

Table 3: Constructs Correlations and Discriminant Validity.

Constructs	BLE	CS	CD	CI	IQ	PS	SQ	TS	TE
Total sample = 242									
BLE	**0.888**								
CS	0.447	**0.864**							
CD	0.745	0.466	**0.892**						
CI	0.644	0.462	0.534	**0.873**					
IQ	0.699	0.484	0.686	0.597	**0.853**				
PS	0.71	0.373	0.697	0.476	0.673	**0.88**			
SQ	0.692	0.492	0.644	0.611	0.785	0.63	**0.842**		
TS	0.661	0.386	0.713	0.518	0.583	0.619	0.598	**0.9**	
TE	0.473	0.635	0.565	0.417	0.571	0.479	0.555	0.432	**0.885**
Students = 128									
BLE	**0.87**								
CS	0.465	**0.834**							
CD	0.757	0.497	**0.881**						
CI	0.726	0.389	0.615	**0.886**					
IQ	0.636	0.461	0.689	0.616	**0.836**				
PS	0.617	0.372	0.643	0.577	0.673	**0.864**			
SQ	0.732	0.497	0.65	0.685	0.803	0.621	**0.841**		
TS	0.747	0.421	0.728	0.596	0.66	0.611	0.704	**0.882**	
TE	0.496	0.539	0.593	0.449	0.588	0.481	0.598	0.482	**0.861**
Teachers = 114									
BLE	**0.907**								
CS	0.447	**0.895**							
CD	0.741	0.485	**0.901**						
CI	0.575	0.524	0.482	**0.859**					
IQ	0.777	0.547	0.679	0.604	**0.872**				
PS	0.8	0.413	0.746	0.404	0.673	**0.895**			
SQ	0.662	0.525	0.636	0.567	0.77	0.637	**0.849**		
TS	0.59	0.38	0.701	0.463	0.516	0.631	0.503	**0.917**	
TE	0.46	0.743	0.535	0.408	0.553	0.472	0.512	0.391	**0.906**

4.1.2. Assessment of Structured Model

The structural model assessment was conducted to examine the hypothesised relationships among constructs as depicted in Figure 1. This evaluation aims to validate the proposed model by analysing the significance and strength of the path relationships. In this study, the path coefficients (β), t-values, and p-values were estimated using PLS-SEM. A non-parametric bootstrapping procedure with 5,000 resamples was applied to assess the statistical significance of the path coefficients. The hypothesis testing results were reported in Table 4.

Table 4: Significance Testing Results of the Structural Model Path Coefficients.

Hypothesis		Total sample = 242				Students = 128				Teachers = 114			
		β	t	p	result	β	t	p	result	β	t	p	result
H1	CS -> BLE	0.03	0.629	0.529	Not supported	0.045	0.69	0.49	Not supported	-0.034	0.488	0.625	Not supported
H2	TE -> BLE	-0.071	1.448	0.148	Not supported	-0.054	0.855	0.393	Not supported	-0.051	0.684	0.494	Not supported
H3	SQ -> BLE	0.129	1.21	0.226	Not supported	0.268	2.395	0.017	Supported	-0.045	0.387		Not supported
H4	IQ -> BLE	0.09	1	0.317	Not supported	-0.148	1.357	0.175	Not supported	0.341	3.178		Supported
H5	PS -> BLE	0.235	2.101	0.036	Supported	0.049	0.578	0.563	Not supported	0.446	3.256	0.001	Supported
H6	TS -> BLE	0.093	1.095	0.274	Not supported	0.237	2.381	0.017	Supported	-0.018	0.215	0.83	Not supported
H7	CI -> BLE	0.218	3.346	0.001	Supported	0.271	2.975	0.003	Supported	0.175	2.487	0.013	Supported
H8	CD -> BLE	0.28	4.121	0	Supported	0.322	3.74	0	Supported	0.178	1.874	0.061	Supported

4.1.3. Multigroup Analysis

To examine whether structural relationships differ across groups, multigroup analysis (MGA) was employed. MGA is a widely adopted method for comparing model parameters between predefined groups (Hair et al., 2017), particularly when exploring variations in the strength or direction of relationships involving categorical moderators (Requez-Cipriano & Mauricio-Andía, 2025). It enables the assessment of whether the associations among constructs hold equivalently across different segments of a population (Yuan & Chan, 2016).

Measurement Invariance of Composite Models (MICOM) analysis was performed to ensure comparability of structural path estimates across different groups before conducting MGA. It consists of three steps recommended by Henseler et al. (2016): configural invariance, compositional invariance, and the equality of composite mean values and variances. A permutation p-value threshold of 0.05 was adopted to indicate significant differences (Latan et al., 2017). As shown in Table 5, the permutation p-values for most constructs exceeded the threshold, supporting the establishment of measurement invariance. Although the IQ construct yielded a p-value of 0.044, its original correlation was as high as 0.998, indicating near-identical composite structures across groups. According to Henseler et al. (2016), partial measurement invariance can be considered acceptable for conducting MGA in borderline cases with very high correlations. Similar interpretations have been adopted in empirical studies (Beltrão et al., 2025).

Table 5: Measurement Invariance of Composite Models Analysis.

	Original correlation	Correlation permutation mean	5.00%	Permutation p value
CS	0.999	0.997	0.988	0.808
TE	0.998	0.998	0.995	0.322
SQ	1	0.999	0.998	0.699
IQ	0.998	0.999	0.998	0.044
PS	1	1	0.999	0.478
TS	0.999	0.999	0.998	0.175
CI	0.999	0.999	0.997	0.409
CD	1	1	0.999	0.437
BLE	1	1	1	0.8

Following this, a bootstrap-based MGA was applied due to its robustness, especially in handling non-normal data distributions and relatively small sample sizes (Chin & Dibbern, 2009). A difference in path coefficients is deemed statistically significant when $p < 0.05$ or $p > 0.95$, given the one-tailed nature of the test (Sarstedt et al., 2011). The detailed MGA results are presented in Table 6.

Table 6: Bootstrap-Based Multigroup Analysis Result.

Hypothesis Path		Teacher (β)	Student (β)	Difference	P-value	Significance
H1	CS -> BLE	-0.034	0.045	-0.078	0.797	No significant difference
H2	TE -> BLE	-0.051	-0.054	0.003	0.489	No significant difference
H3	SQ -> BLE	-0.045	0.268	-0.313	0.969	Significantly different
H4	IQ -> BLE	0.341	-0.148	0.488	0.001	Significantly different
H5	PS -> BLE	0.446	0.049	0.397	0.009	Significantly different
H6	TS -> BLE	-0.018	0.237	-0.256	0.969	Significantly different
H7	CI -> BLE	0.175	0.271	-0.096	0.796	No significant difference
H8	CD -> BLE	0.178	0.322	-0.145	0.873	No significant difference

4.2. Asymmetric Analysis Result

The causal relationships derived from PLS-SEM are typically linear in nature. However, the effectiveness of BL may be shaped by complex and nonlinear interactions among multiple determinants in practice. To address this, the present study further employs fsQCA to examine the configurational effects of factors on the effectiveness of BL. In the fsQCA procedure, the eight latent constructs were treated as antecedent conditions, and BL effectiveness was designated as the outcome, enabling a configurational analysis of how combinations of conditions result in the observed outcomes. Before conducting the fsQCA analysis, survey data were converted into fuzzy sets with membership scores ranging from 0 to 1 to improve interpretability. As all antecedent variables consisted of multiple items, the mean of each variable was computed prior to calibration. Following Ragin (2009), three anchors were set for calibration: full membership (95%), full non-membership (5%), and the crossover point (50%), as detailed in Table 7.

Subsequently, NCA was conducted to assess whether any single condition constituted a necessary antecedent for the outcome. Following Dul (2016), a condition is considered necessary only when the consistency value exceeds the threshold of 0.90. The results in Table 8 indicate that all conditions fell below this threshold and thus did not qualify as necessary conditions, which supports the appropriateness of conducting a sufficiency analysis based on causal combinations.

Table 7: Calibration Anchors for Each Variable.

	Total sample = 242			**Student = 128**			**Teacher = 114**		
	95%	50%	5%	95%	50%	5%	95%	50%	5%
CS	5.00	4.00	2.33	5.00	4.00	2.45	5.00	4.00	2.33
TE	5.00	4.33	3.00	5.00	4.33	3.00	5.00	4.00	2.67
SQ	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.00	2.41
IQ	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.00	2.75
PS	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.00	2.66
TS	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.00	2.67
CI	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.17	3.00
CD	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.00	2.67
BLE	5.00	4.00	3.00	5.00	4.00	3.00	5.00	4.00	3.00

Table 8: Necessary Condition Analysis Result.

Constructs	**Total sample = 242**		**Students = 128**		**Teachers = 114**	
	Consistency	**Coverage**	**Consistency**	**Coverage**	**Consistency**	**Coverage**
CS	0.72388	0.815296	0.67508	0.862106	0.769924	0.773911
TE	0.694573	0.785473	0.711541	0.79207	0.786991	0.756773
SQ	0.775446	0.891262	0.841536	0.884712	0.793109	0.873249
IQ	0.775446	0.895835	0.77759	0.871992	0.79005	0.919775
PS	0.788713	0.901791	0.804515	0.882751	0.795685	0.916033
TS	0.785789	0.884651	0.806478	0.896632	0.784093	0.865778
CI	0.872958	0.814818	0.847567	0.843427	0.836902	0.801171
CD	0.768775	0.915231	0.807741	0.904239	0.744969	0.923553

The truth tables for sufficiency analysis were then constructed to identify combinations of conditions that contribute to the outcome. The rows with fewer than two and one cases were eliminated separately, consistent with the recommendations for large-sample (N > 150) and mid-sample studies (50 < N < 150) proposed by Fiss (2011). Using the Quine-McCluskey algorithm, parsimonious, intermediate, and complex solutions were generated. The parsimonious and intermediate solutions were selected for interpretation as recommended by previous literature, to identify the core conditions, peripheral conditions, and sufficient configurations (Rahman et al., 2025). The conditions that appear in both parsimonious and intermediate solutions are identified as core conditions, which serve as stable and strong sufficient conditions. In contrast, the conditions that appear only in the intermediate solution are referred to as peripheral conditions, which serve as supporting sufficient conditions (Dabbous et al., 2024). The parsimonious solution results were presented in Table 9.

The intermediate solutions for configurations were generated, as presented in Table 10, Table 11, and Table 12, in which the symbol ● indicates "presence of condition", ○ denotes "absence of condition", and the blank space indicates "do not care condition". The results indicated that course interaction (CI) serves as the only core condition across groups, with a raw coverage of 0.872958, indicating that this condition explains 87.3% of the cases. The high consistency level (0.814818) further supports the sufficiency of this condition in producing the outcome. Group-specific analyses further revealed technology experience (TE) as an additional core condition among students, while other factors functioned as peripheral conditions, enhancing or moderating the outcome under specific configurations. For the teacher groups, the parsimonious solution identified a combination of multiple sufficient conditions, including course interaction (CI), computer self-efficacy (CS), technology experience (TE), system quality (SQ), policy support (PS), technical support (TS), and course design (CD). It explains that BL effectiveness can be achieved through the synergistic interaction of these factors, in which CI remains the most explanatory and influential core condition, with the raw coverage of 0.836902, highlighting its centrality in facilitating effective blended teaching practices.

Table 9: Parsimonious Solutions.

Total sample = 242	Raw coverage	Unique coverage	Consistency
CI	0.872958	0.872958	0.814818
solution coverage: 0.872958			
solution consistency: 0.814818			
Students = 128			
TE	0.711541	0.0755856	0.79207
CI	0.847567	0.211612	0.843427
solution coverage: 0.923152			
solution consistency: 0.768414			
Teachers = 114			
CI	0.836902	0.0169054	0.801171
CS	0.769924	0.00209302	0.773911
TE	0.786991	0.00144899	0.756773
SQ	0.793109	0.00338107	0.873249
PS	0.795685	0	0.916033
TS	0.784093	0.00885528	0.865778
CD	0.744969	0.000804961	0.923553
solution coverage: 0.982933			
solution consistency: 0.69108			

Table 10: Configurations of Conditions Result (Total Sample = 242).

Configuration	CS	TE	SQ	IQ	PS	TS	CI	CD	Raw coverage	Unique coverage	Consistency
1	●		●	●	●	●	●	●	0.456978	0.0329037	0.990416
2		●	●	●	●	●	●	●	0.443187	0.0377006	0.985336
3	○	○	○	○	○	○	●	○	0.310748	0.122546	0.83673
consistency cut-off: 0.83673 solution coverage: 0.625693 solution consistency: 0.903756											

Table 11: Configurations of Conditions Result (Students = 128).

Configuration	CS	TE	SQ	IQ	PS	TS	CI	CD	Raw coverage	Unique coverage	Consistency
1	○	●	●	●	●	●	●		0.364745	0.0471182	0.984854
2	●		●	●	●	●	●	●	0.446501	0.117375	0.989127
3	○	●	○	○	○	○	○	○	0.270088	0.0307111	0.866007
4	○	○	○	○	○	○	●	○	0.315383	0.037302	0.864003
5	○	○	○	●	●	○	●	○	0.268125	0.00939566	0.974516
6	○	○	○	○	●	●	●	●	0.278783	0.012621	0.991027
7	○	○	●	●	○	●	●	●	0.260132	0.00448751	0.979409
consistency cut-off: 0.864003 solution coverage: 0.675641 solution consistency: 0.891562											

Table 12: Configurations of Conditions Result (Teachers = 114).

Configuration	CS	TE	SQ	IQ	PS	TS	CI	CD	Raw coverage	Unique coverage	Consistency
1	●	●		○	○	●	●	○	0.273386	0.00949919	0.906567
2	●	●		●	●	●	●	●	0.46627	0.184189	0.984364
3	○	○	○	○	○	○	●	○	0.278699	0.0437931	0.826648
4	●	●	○	○	○	○	○	○	0.241507	0.0130413	0.822369
5	○	●	○	●	○	○	●	○	0.242956	0.00740618	0.946082
6	○	○	●	○	●	●	○	●	0.20029	0.0196426	0.9803
7	●	●	●	●	○	○	●	○	0.282885	0.0080502	0.94666
8	●	●	○	○	●	●	○	●	0.229915	0.00740618	0.937008
9	●	●	○	●	○	○	●	●	0.242795	0.00483012	0.958069
10	●	●	●	●	●	○	○	●	0.242151	0.0222186	0.970949
consistency cut-off: 0.822369 solution coverage: 0.718564 solution consistency: 0.857609											

The configuration results revealed high overall solution consistencies of 0.903756 (total sample), 0.891562 (students), and 0.857609 (teachers), all exceeding the recommended threshold of 0.75. These values indicated the robustness of the findings and a highly consistent set-theoretic relationship, confirming that the identified configurations are strongly linked to high BL effectiveness. The solution coverages are also substantial, with values of 0.625693, 0.675641, and 0.718564, respectively, demonstrating the strong explanatory capacity of the models.

5. DISCUSSION

This study employed a mixed-method approach, combining PLS-SEM and fsQCA, to examine how individual, technological, institutional, and instructional dimensions influence the effectiveness of BL from both student and teacher perspectives.

The PLS-SEM results revealed a consistent pattern across groups at the instructional dimension. Both course interaction (CI) ($\beta = 0.271$, $p < 0.01$; $\beta = 0.175$, $p < 0.05$) and course design (CD) ($\beta = 0.322$, $p < 0.01$; $\beta = 0.178$, $p < 0.1$) exerted significant positive effects on BL effectiveness. The MGA results further confirmed that these effects did not significantly differ between groups, indicating a shared perception of the importance of structured content and interactive learning environments in BL contexts. These findings align with prior research that emphasises the centrality of instructional practices in interaction with technology-supported learning (Kintu et al., 2017). A well-structured course design ensures coherence and alignment among learning objectives, activities, and assessments. At the same time, an interactive environment fosters personalised support from instructors (H. Huang et al., 2022), encourages participation, and facilitates knowledge construction (Zhu et al., 2021). Collectively, these instructional features constitute essential determinants for achieving effective and sustainable BL implementation in the Thai higher education context.

By contrast, notable divergences were observed at the technological and institutional dimensions, as MGA results indicated significant disparities ($p < 0.05$ or $p > 0.95$). Teachers prioritised more on information quality (IQ) ($\beta = 0.341$, $p < 0.01$) and policy support (PS) ($\beta = 0.446$, $p < 0.01$), reflecting their role as content developers and policy implementers. This pattern is consistent with Zhao and Song (2021) and supports the findings of Dahri et al. (2024), who argue that accurate, relevant, and well-structured content promotes engagement, collaboration, and active participation, while supportive institutional policies stimulate pedagogical innovation. Instructors were more motivated to invest effort and innovate when university policies explicitly integrated BL into teaching evaluation systems or offered administrative support for course development. In contrast, students appeared less sensitive to such macro-level support mechanisms. Conversely, students placed greater emphasis on system quality (SQ) ($\beta = 0.268$, $p < 0.05$) and technical support (TS) ($\beta = 0.237$, $p < 0.05$), findings that are consistent with those of Kintu et al. (2017) and Chiu (2021). This highlights that learners perceive the stability, usability, and accessibility of the e-learning platform, as well as the availability of timely technical assistance, as crucial for ensuring a seamless learning process. These factors minimise the technological barriers and facilitate academic performance. Many higher education institutions in Thailand have established IT support systems, including faculty-based IT departments and dedicated learning support centres. Such systemic support enables teachers to shift attention away from technical issues and instead concentrate on policy guidance and the quality of instructional content. Although students also benefit from these institutional systems, their learning experiences depend more directly on the functionality of the e-learning system and the availability of technical assistance.

Interestingly, neither computer self-efficacy (CS) nor technology experience (TE) exerted a significant direct effect across groups ($p > 0.05$), a finding that diverges from studies that emphasise their role in adoption processes (Prifti, 2022). A reasonable explanation is that in contexts where digital exposure is widespread and educational technologies are relatively mature, technological capabilities may no longer function as primary drivers of BL effectiveness. This interpretation aligns with Cao (2023) and Dziuban et al. (2018), who argue that BL effectiveness is shaped by learners' diverse backgrounds, including prior educational experiences and geographic circumstances. The fundamental infrastructure and digital literacy are treated as baseline conditions rather than barriers in the mature technological environments. In other words, once technological infrastructure and digital literacy reach a certain threshold, their marginal contribution to learning effectiveness diminishes. This finding extends the applicability of other models by suggesting that the roles of CS and TE are not uniform and directly significant, but may vary with contextual maturity, particularly in the BL institutional settings that are mature. Taken together, the PLS-SEM findings reveal a multi-layered structure of determinants. Instructional features function as universal drivers across groups, whereas institutional and technological factors exhibit role-specific salience. Individual factors, once considered primary enablers, appear to have diminished explanatory power under conditions of BL maturity in higher education.

The fsQCA analysis further complement the understanding by uncovering the configurational pathways to BL effectiveness. The NCA result revealed that no single condition met the threshold of necessity (consistency > 0.9), confirming that BL effectiveness is a multi-causal phenomenon. For the total sample (Table 10), three sufficient configurations were identified. Among them, configurations 1 and 2 exhibited high consistency values of 0.990416 and 0.985336, respectively. The raw coverages are 0.456978 and 0.443187, explaining approximately 45% of the cases. A particularly noteworthy finding was that CS and TE appeared in these two sufficient solutions, separately. While PLS-SEM revealed no significant direct effects for these individual-level factors on BL effectiveness, the fsQCA findings demonstrated that their contributions become visible when embedded with institutional and instructional supports. In other words, the effects of CS and TE are conditional on contextual fit: when SQ, IQ, PS, TS, CI, and CD are well provisioned, either high CS or high TE can serve as complementary conditions for achieving high BL effectiveness. Conversely, configuration 3 indicated that the presence of CI alone was sufficient to achieve high BL effectiveness even in the absence of most supportive conditions. These results illustrated the fsQCA principle of equifinality, whereby multiple distinct causal paths can lead to the same outcome (Salonen et al., 2021). Moreover, it was noted that CI consistently appeared across all pathways with the same directional relationship, marking it as the most stable core condition. This finding is consistent with prior studies (Chen, 2025; Dong, 2025), which highlight the prominent role of course interaction in the learning process. As articulated by Gao et al. (2024), the prompt and effective instructor-student engagement mitigates transactional distance, thereby improving learning efficiency, accelerating knowledge acquisition, and supporting more effective problem-solving outcomes (Makri et al., 2020).

Group-specific fsQCA solutions offer additional insights. Among students, seven sufficient configurations were identified (Table 11). Configuration 2 demonstrates the highest raw coverage (0.446501) with consistency (0.989127), explaining nearly 45% of the cases. It highlights the combined presence of CS, SQ, IQ, PS, TS, CI, and CD, which form a robust and sufficient pathway for achieving BL effectiveness. Interestingly, while TE was not statistically significant in the PLS-SEM analysis for BL effectiveness, it emerged as a core condition in the fsQCA configurations. This apparent discrepancy suggests that TE may not exert a strong independent effect on BL effectiveness across all cases, but it becomes a critical enabler in combination with other conditions. Table 12 displays the ten configurations for the teacher group. Configuration 2 exhibits the highest raw coverage (0.46627) and consistency (0.984364). Its unique coverage is 0.184189, implying that around 18.5% of the cases are exclusively explained by this combination. These results reinforced the centrality of PS, TS, CI, and CD as core conditions for teachers. As noted by Zhao and Song (2021), effective BL instruction relies on multifaceted support, encompassing instructional guidance, adequate funding and infrastructure, institutional policy support, and technical assistance. Furthermore, systematic support provided through professional development activities and periodic training workshops constitutes a crucial component in facilitating the successful implementation of BL (Mohammadi et al., 2025). Consequently, the mechanisms for achieving BL effectiveness differ across stakeholder groups, suggesting that differentiated and group-specific support strategies are necessary.

In summary, these findings highlight that BL effectiveness is not driven by single causal factors but emerges from the interplay of multiple conditions. PLS-SEM uncovered linear and statistically significant effects, whereas fsQCA provided a complementary relationship by revealing equifinal pathways, which are different combinations of conditions that are sufficient to produce the outcome. The integration and complementarity of approach underlines the critical role of systems thinking and configurational logic, implying that higher education policy and practice should emphasise the coordinated optimisation of multidimensional conditions to promote effective and sustainable BL initiatives.

6. CONCLUSION

This study examined the key determinants of BL effectiveness in Thai higher education from dual stakeholder perspectives, employing a hybrid analytical approach integrating PLS-SEM and fsQCA. The findings offer both theoretical and practical insights that advance understanding of technology-supported learning in higher education.

Theoretically, this research not only validates the multidimensional model of BL effectiveness but also extends the understanding of how different stakeholders experience and engage with the BL environment. By combining symmetric and asymmetric approaches, the study identifies "what" matters most by demonstrating the net effects of factors and "how" different conditions combine to be effective through configurations. This hybrid perspective illustrates that even when certain factors are absent, other synergistic combinations of conditions can still sustain BL effectiveness, thereby overcoming the limitations of traditional single-factor significance testing.

Practically, the results reveal both convergence and divergence in stakeholder perceptions. The well-designed instructional and interactive course emerges as a commonly recognised determinant for sustaining BL effectiveness in Thai higher education. This highlights the need for higher education institutions to prioritise investment in faculty development programs that strengthen teachers' capacity for course design and pedagogical skills, as well as promote personalised instructional support to learners. The technological and institutional dimensions diverge between groups. The system quality and technical support appear to exert a more substantial influence on BL effectiveness among students, whereas policy support and information quality play a larger role among teachers. This divergence reflects role-specific priorities in strategic planning: enhancing system responsiveness, stability, and ease of use, and constructing learner-centred technical support to improve students' engagement and performance, while strengthening policy frameworks, providing administrative support on BL initiative, and supporting high-quality content design to optimise teachers' instructional effectiveness. Although individual dimension factors appear to have no direct influence on both groups, the sufficient configuration analysis revealed that they remain core conditions when aligned with complementary contextual and institutional supports.

Future research could validate the proposed model across diverse cultural and educational contexts to examine potential variations in key determinants. Additionally, expanding the stakeholder scope to include administrators and technical support staff, employing longitudinal or cross-institutional designs, and integrating contextual variables such as institutional culture could further refine the model and strengthen the generalizability of the findings.

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