A STUDY ON THE INFLUENCING FACTORS AND MECHANISMS OF MULTIDIMENSIONAL EVALUATION SYSTEMS ON UNDERGRADUATE DEEP LEARNING EFFECTS*

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Abstract

In 21st-century higher education, fostering deep learning is essential for developing critical thinking, creativity, and lifelong learning. This study examined the impact of the Multidimensional Evaluation System (MES) on undergraduates' deep learning, identified key influencing factors, and provided implementation recommendations. A mixed-methods design included a survey of 801 students and interviews with 10 instructors. CFA confirmed a seven-dimensional deep learning construct with 43 indicators (GFI = .958, AGFI = .953, RMSEA = .000, RMR = .020). Overall deep learning was high (M = 3.680), especially in creative thinking, problem-solving, lifelong learning, and thinking ability. Qualitative findings indicated that MES promotes academic, cognitive, social, and emotional growth via project-based, peer/self-assessment, and performance tasks, supported by motivation, feedback, and collaboration. Challenges included unclear rubrics and limited teacher training. Recommendations include refining criteria, targeted professional development,

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and institutional support. The study validates a multidimensional deep learning model and offers practical strategies for achieving 21st-century educational goals.

Keywords: Influencing Factors, Mechanism of Action, Multidimensional Evaluation Systems, Deep Learning Effects

Introduction

In the 21st century, rapid advances in information technology have reshaped higher education by expanding access to diverse resources, methods, and environments. These opportunities also expose the limitations of traditional teaching and assessment in fostering deep learning, which enables learners to integrate and apply knowledge critically for higher-order thinking and problem-solving (Brandt, Dadey, & Evans, 2024; Herlinawati et al., 2024). In today's knowledge economy, graduates must demonstrate not only foundational mastery but also creativity, independent thinking, and lifelong learning (Katsamakas, Pavlov, & Saklad, 2024; Wu et al., 2024). This highlights the urgent need for evaluation systems that promote both academic excellence and holistic development.

The Multidimensional Evaluation System (MES) addresses this need by assessing cognitive, affective, and behavioral domains within a unified framework. Drawing on Gardner's Multiple Intelligences, Biggs and Collis's SOLO Taxonomy, and Sternberg's Successful Intelligence, MES integrates diverse perspectives on learner diversity, cognitive complexity, and real-world problem-solving. Unlike fragmented applications, MES synthesizes these theories to evaluate learning strategies, creativity, and authentic application of knowledge. Research suggests multidimensional assessments enhance motivation, collaboration, and feedback, which are vital for deep learning (Entwistle, 2020; Mehdi & Bahraman, 2022).

Although deep learning theory is well established (Marton & Säljö, 1976; Biggs, 2017; Entwistle, 2001), limited empirical research has examined the specific influence of MES in undergraduate contexts. This study therefore aims to: (1) investigate the impact of MES on undergraduates' deep learning outcomes, (2) analyze key factors and mechanisms shaping its effectiveness, and (3) propose recommendations for higher education implementation. Using a mixed-methods design, it evaluates practices, challenges, and enablers, while considering both positive and potential negative effects. The findings are expected to advance theory, inform policy, and guide practice toward achieving 21st-century learning goals.

Objectives

1. To explore the specific impact of the multi-dimensional evaluation system on the in-depth learning effect of undergraduates;

2. To analyze the key factors and mechanisms that affect the effectiveness of deep learning;

3. Suggestions for implementing a multidimensional assessment system for undergraduate students.

Literature Review

The Multidimensional Evaluation System (MES) integrates cognitive, emotional, social, behavioral, and creative domains to address limitations of traditional assessments, emphasizing formative feedback, reflection, and performance-based tasks (Biggs & Tang, 2011; Fullan & Langworthy, 2014; Bertalanffy, 1968; Vygotsky, 1978; Gardner, 1983; Messick, 1995). Using portfolios, rubrics, peer-assessment, and projects, MES enhances engagement, motivation, and learner strengths while fostering critical thinking, creativity, collaboration, and professional readiness (Temur, 2007; Hattie & Timperley, 2007; Zhao, 2012).

Deep learning involves integrating new knowledge with prior understanding to develop comprehension, application, higher-order thinking, problem-solving, and creativity (Marton & Säljö, 1976; Biggs, 2017; Entwistle, 2008). Motivation, metacognition, emotional engagement, active learning, collaborative projects, and formative assessment support reflection and self-regulation (Pintrich, 2000; Schunk & DiBenedetto, 2020; Biggs & Tang, 2011; Freeman et al., 2014; Hattie & Timperley, 2007).

The development of deep learning is shaped by personal, social, and environmental factors, including cognitive readiness, self-regulation, effective teaching, feedback, peer collaboration, and supportive environments (Bronfenbrenner, 1979; Dweck, 2006; Vygotsky, 1978). Intrinsic motivation, authentic assessment, and technology integration further enhance curiosity, autonomy, and personalized learning, reinforcing holistic, meaningful, and transferable learning outcomes (Deci & Ryan, 2000; Nicol & Macfarlane-Dick, 2006; Marton & Säljö, 1976; Fullan & Langworthy, 2014).

Methodology

This study employed a mixed-methods design, combining quantitative and qualitative approaches to explore the influence of multidimensional evaluation systems (MES) on undergraduate deep learning outcomes.

1. Population and Sample

The research population consisted of 3,000 undergraduate students and 1,493 full-time faculty members at Yunnan Minzu University in 2025. The sample included 801 undergraduates selected through quota sampling, determined according to Taro Yamane's (1973) formula at a 95% confidence level with a 0.05 margin of error. In addition, 10 full-time instructors were selected using purposive sampling. Eligible instructors were from the Faculties of Engineering, Humanities and Social Sciences, Arts and Humanities, and Education, with at least five years of teaching experience and holding an academic position of lecturer or above.

2. Research Instruments and Quality Assurance

Two research instruments were employed: a structured questionnaire for undergraduates and an in-depth interview protocol for instructors. The questionnaire included demographic information and 43 items measuring seven MES-based deep learning dimensions (knowledge, thinking ability, learning attitude, practical ability, creative problem-solving, teamwork and communication, and lifelong technical learning) on a five-point Likert scale. The interview protocol explored instructors' understanding of MES, implementation practices, impacts on student abilities and motivation, and suggestions for improvement. Instrument validity was confirmed by five experts, with the Index of Item-Objective Congruence (IOC) ranging from 0.80 to 1.00. Reliability analysis using Cronbach's alpha indicated high internal consistency across all dimensions.

3. Data Collection

Permission for data collection was obtained from Yunnan Minzu University and ethical clearance was granted by the Human Research Ethics Committee. Questionnaires were distributed to the student sample, while in-depth interviews were conducted with selected faculty members. Data collection included verification of completeness of responses, and interviews were recorded, transcribed, and anonymized to ensure confidentiality.

4. Data Analysis

Quantitative data were analyzed using SPSS and AMOS, applying descriptive statistics (mean, SD) and inferential tests (t-test, ANOVA) to examine group differences by origin, year, faculty, and GPA. Confirmatory Factor Analysis (CFA) tested construct validity using indices such as KMO, Bartlett's test, factor loadings, χ^2/df, GFI, AGFI, RMSEA, and SRMR, while reliability was assessed with Cronbach's alpha and correlations. Qualitative interview data were examined through thematic analysis to identify patterns in teachers' perceptions of MES and its impact on students' learning, emotions, and motivation. Integration of both strands ensured triangulated insights into MES effectiveness in supporting deep learning.

Results

1 . The Results of Deep Learning Levels among Undergraduate Students

In this study, 801 valid questionnaires were distributed and obtained by taking Yunnan Minzu University as the survey object, and the basic information of the respondents is shown in Table 1

Table 1 presents the mean (M), standard deviation (S.D.), and interpretation of the levels of deep learning outcomes (n = 801).

No.	Items	*M*	S.D.
1	Knowledge Mastery	3.642	0.930
2	Thinking Ability	3.703	0.911
3	Learning Attitude	3.703	0.928
4	Practical Ability	3.591	0.946
5	Innovative Thinking and Problem Solving	3.774	1.008
6	Teamwork and Communication Skills	3.606	0.866
7	Continuous Learning in Technology	3.742	1.000
	Overall	**3.680**	**0.784**

According to Table 1, The analysis revealed that undergraduate students at Yunnan Minzu University demonstrated a moderately high level of deep learning outcomes (M = 3.680, SD = 0.784). The highest mean score was found in creative thinking and problem-solving (M = 3.774, SD = 1.008), The lowest mean score was in practical ability (M = 3.591, SD = 0.946).

The results of the independent samples t-test and one-way ANOVA indicated that there were no statistically significant differences in undergraduate students' deep learning outcomes across the variables of year of study, faculty, GPA, and place of origin, as shown in Table 2.

Category	Remark
Year of Study	No significant difference (F = 1.205, p = .307)
Faculty	No significant difference (F = 1.048, p = .402)
GPA	No significant difference (F = 0.273, p = .895)
Place of Origin	No significant difference (t = 1.568, p = .117)

According to Table 2, Across all categories year of study, faculty, GPA, and place of origin no statistically significant differences were found at the .05 level. This indicates that deep learning outcomes were relatively consistent among students regardless of demographic or academic background.

2. Confirmatory Factor Analysis of Deep Learning Outcomes

All 43 deep learning items were analyzed using correlation coefficients (r), sampling adequacy (MSA), mean (M), and standard deviation (S.D.). Correlations ranged from .305 to .714, all significant at the .01 level. Bartlett's Test of Sphericity confirmed that the correlation matrix was not an identity matrix (χ^2 = 25,352.044, df = 903, p = .000), and the KMO measure was .985, with individual MSA values between .970 and .991, indicating suitability for CFA, as shown in Table 3.

Table 3 Assessment of Preliminary Assumptions for Confirmatory Factor Analysis

Assessment of Preliminary Assumptions	χ^2	KMO	df	p-value
Bartlett's Test	25352.044	.985	903	.000*

* Statistically significant at the .05 ($p < .05$)

First-Order Confirmatory Factor Analysis

The first-order CFA validated the deep learning instrument with 7 components and 43 indicators. Standardized factor loadings ranged from 0.654 to 0.846, all significant. Model fit indices indicated excellent fit: χ^2 = 749.996, p = .987; χ^2/df = 0.893; GFI = .958; AGFI = .953; RMSEA = .000; SRMR = .016. The seven components measured were: Knowledge (3 items), Thinking Ability (12), Learning Attitudes (10), Practical Ability (3), Creative Thinking and Problem Solving (3), Teamwork and Communication Skills (9), and Lifelong Learning in Technology (3), demonstrating alignment with empirical data.

3. Results of an In-Depth Interview on Multidimensional Evaluation Systems

Teachers expressed varied familiarity with the multidimensional evaluation system but shared a common view of its differences from traditional assessment. They emphasized its holistic focus on knowledge, skills, attitudes, creativity, and teamwork, beyond mere test scores. The system promotes process-oriented assessment through peer evaluation, self-reflection, projects, and classroom participation. Instructors reported that it enhanced students' motivation, emotional engagement, and learning enjoyment. Teachers observed significant contributions to students' critical thinking, innovation, and practical problem-solving abilities. Implementation examples included programming, arts, sports, and social research projects that integrated theory with practice.

Challenges noted were unclear assessment criteria, lack of transparency, and teachers' need for training. Overall, teachers strongly supported the system as fostering deep learning and 21st-century skills.

Discussion

This study confirms that deep learning among undergraduates at Yunnan Minzu University can be effectively assessed using a multidimensional model. Overall, students demonstrated a relatively high level of engagement with deep learning (M = 3.680, SD = 0.784), indicating they engage in meaningful, reflective, and critical learning beyond rote memorization. Among the seven dimensions, students scored highest in creative thinking and problem-solving, lifelong learning in technology, thinking ability, and learning attitude, reflecting strong capacities for adaptive, autonomous, and innovative learning (Mezirow, 1991; Bransford et al., 2000). High scores in items such as mindset adjustment after setbacks (M = 3.963) and awareness of technological trends (M = 3.940) further demonstrate these dispositions.

No statistically significant differences were found across demographic variables, including academic year, GPA, faculty, or place of origin, suggesting that deep learning is broadly accessible and not constrained by background factors (Florian & Black-Hawkins, 2011). Confirmatory factor analysis validated the seven-dimensional model, with excellent fit indices (GFI = .958; RMSEA = .000), confirming that deep learning is a multifaceted construct requiring comprehensive evaluation approaches (Entwistle & Peterson, 2004).

Qualitative data from instructor interviews reinforced the quantitative findings, indicating that the Multidimensional Evaluation System (MES) is widely understood and positively perceived. MES promotes holistic assessment of knowledge, skills, attitudes, emotional intelligence, and creativity, aligning with learner-centered and performance-based evaluation practices (Birenbaum, 2003). Educators reported applying MES across disciplines using classroom observation, projects, peer and self-assessments, and performance-based tasks, supporting the development of higher-order thinking skills such as critical thinking, problem-solving, and innovation (Zhao, 2012; Shavelson & Baxter, 1992).

MES also enhanced student motivation, engagement, and emotional commitment, fostering self-expression, applied learning, and innovation. However, challenges such as unclear rubrics, lack of transparency, and insufficient teacher training were identified, highlighting the need for institutional support, professional development, and clear guidelines. Overall, MES provides a flexible, meaningful, and effective framework for promoting holistic development, bridging theory and practice, and supporting the shift toward 21st-century learning paradigms (Darling-Hammond & Adamson, 2014).

Recommendation

Recommendations for the Current Study

Undergraduates showed strengths in creativity, problem-solving, and lifelong learning. To sustain this, deep learning should be assessed through multidimensional methods encompassing knowledge, skills, attitudes, teamwork, and innovation. Project-based, peer, and performance assessments, supported by transparent criteria and teacher training, are recommended to foster self-directed learning, creativity, and higher-order thinking.

Recommendations for Future Research

Future studies should include students from multiple institutions and regions to examine deep learning in diverse contexts. Research should explore additional factors such as teaching methods, educational technology, and learning environments, as well as long-term effects of MES on critical thinking, creativity, self-directed learning, academic achievement, and workplace adaptability.

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