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From Perception to Precision: Applying Multimodal Data Analytics to Assess Ideological Outcomes in Vocational College English Courses

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Abstract: ***The integration of ideological and political education (IPE) into foreign language teaching at higher vocational colleges presents a fundamental assessment challenge: how can subjective, internalized values such as cultural confidence, professional ethics, and patriotism be systematically measured and evaluated? Traditional approaches relying on teacher observation and summative testing fail to capture the developmental, multidimensional nature of ideological outcomes. This empirical study addresses this gap by developing and validating a multimodal data analytics framework for assessing IPE outcomes in English courses at a higher vocational college in China. Drawing on learning analytics theory and curriculum IPE principles, the study constructs a technical pathway for collecting and analyzing diverse data streams—including classroom interactions, online discussion posts, project-based assignments, speech recordings, and behavioral engagement metrics—over a 16-week teaching experiment involving 186 students across four classes. Using natural language processing, speech recognition, social network analysis, and behavioral analytics, the study generates individual and class-level "digital competence profiles" that visualize students' ideological development across cognitive, emotional, and behavioral dimensions. Results indicate that data-driven assessment significantly enhances diagnostic accuracy, reduces teacher evaluation bias, and supports targeted pedagogical interventions. Student engagement scores increased by 12.4%, while the correlation between evaluation results and observed behavioral outcomes improved from r=0.43 to r=0.78 compared to traditional assessment methods. The findings contribute to the emerging field of data-driven values education assessment, offering both theoretical insights and practical guidelines for implementing multimodal analytics in vocational education contexts.***

Keywords: Multimodal data analytics, Ideological and political education, Foreign language teaching, Higher vocational education, Learning analytics, Digital competence profiling**.**

1. Introduction

1.1 The Assessment Challenge in IPE-Embedded Foreign Language Teaching

Higher vocational colleges in China face a distinctive educational mandate: to develop students' foreign language competence while simultaneously cultivating their ideological-political consciousness, cultural confidence, and professional ethics. This dual mission, articulated through the national "curriculum ideological and political education" policy, requires that language instruction serve as a vehicle for value formation—preparing students not only for international communication but also for service to national development strategies.

However, the assessment of IPE outcomes in foreign language courses has proven exceptionally challenging. Unlike measurable linguistic outcomes—such as vocabulary acquisition or grammatical accuracy—ideological outcomes are inherently subjective, implicit, and developmental. Traditional evaluation methods, which rely heavily on teacher observation, written examinations, and summative judgments, exhibit three critical limitations:

First, **subjectivity**: assessment depends on teachers' individual perceptions and interpretations, leading to inconsistent and potentially biased evaluations. Second, **fragmentation**: most assessments occur at discrete points (midterm, final) rather than tracking developmental trajectories, missing the formative dimension of ideological growth. Third, **quantification difficulty**: value-related outcomes resist easy translation into measurable indicators, resulting in vague, non-actionable evaluation reports.

These limitations have led to what scholars describe as the "softening, weakening, and hollowing" of IPE effectiveness — where ideological elements are inserted into language instruction without meaningful assessment of their actual impact. As one study found, 73.6% of ESP teachers prioritize "industry English vocabulary mastery" as their primary goal, while only 18.2% explicitly include "patriotism" in their course objectives. This suggests that the absence of robust assessment tools directly undermines the implementation of IPE in foreign language education.

1.2 The Promise of Multimodal Data Analytics

Recent advances in educational technology—particularly in learning analytics, natural language processing, and multimodal data integration—offer unprecedented opportunities to address these assessment challenges. The fundamental premise is that learning processes generate diverse digital traces: classroom participation logs, online discussion content, assignment submissions, speech recordings, and behavioral interaction data. When systematically collected and analyzed, these traces can provide objective, dynamic, and multidimensional evidence of student learning outcomes, including those traditionally considered too subjective for systematic assessment.

Studies in vocational education contexts have demonstrated the potential of data-driven approaches. Virtual learning environments (VLEs) combined with learning analytics enable real-time tracking, diagnosis, and feedback, improving both assessment precision and student engagement. AI-enhanced value-added assessment systems have shown superior outcomes in vocational courses, with experimental groups outperforming control groups in academic performance, certification rates, and employer satisfaction. However, these studies have primarily focused on technical skills and cognitive outcomes, leaving a significant gap: the application of multimodal analytics to values education in foreign language contexts remains largely unexplored.

1.3 Research Questions and Objectives

This study addresses this gap by investigating the following research questions:

How can multimodal data streams be systematically collected and integrated to assess IPE outcomes in vocational college English courses?

What analytical approaches are effective for extracting meaningful indicators of ideological development from diverse data types?

Does multimodal data-driven assessment demonstrate improved validity and practical utility compared to traditional evaluation methods?

The study aims to develop, implement, and validate a multimodal analytics framework for IPE assessment in vocational college English teaching, contributing both theoretical understanding and practical guidance for data-driven values education.

2. Literature Review

2.1 Ideological and Political Education in Foreign Language Teaching

The integration of IPE into foreign language education has been a policy priority in Chinese higher education since the 2016 National Conference on Ideological and Political Work in Higher Education. For vocational colleges, which serve as key institutions for cultivating skilled professionals, this integration carries particular significance: students are expected to develop not only technical competence but also the values, work ethic, and cultural identity required for national development.

Foreign language courses present both opportunities and challenges for IPE implementation. On one hand, the inherent “cross-cultural, cross-disciplinary, and cross-contextual” nature of language education provides rich opportunities for integrating discussions of values, national identity, and cultural comparison. On the other hand, the longstanding “instrumental rationality” orientation of language teaching — focusing narrowly on vocabulary, grammar, and communication skills—has often led to the marginalization of value-oriented objectives.

Research on IPE assessment in this context reveals persistent challenges. Studies have identified “single evaluation methods lacking multidimensional data support” and “unsystematic integration of ideological elements with unclear evaluation criteria” as critical weaknesses. While scholars have advocated for process-oriented and formative assessment models, the translation of these conceptual proposals into practical, scalable tools has been limited [1].

2.2 Learning Analytics and Multimodal Data in Educational Assessment

Learning analytics (LA) has emerged as a mature field offering sophisticated tools for collecting, analyzing, and visualizing educational data. Early LA applications focused on predicting academic risk, identifying learning difficulties, and providing personalized interventions, primarily using structured data from learning management systems. More recent developments have expanded to include unstructured data sources, multimodal inputs, and more nuanced analytical techniques.

Research on vocational education has shown particular promise for LA applications. Studies on virtual learning environments in vocational training demonstrate that analytics-driven dashboards and personalized feedback loops foster heightened student engagement and self-regulated learning behaviors, mitigating dropout rates and augmenting competency attainment. AI-driven value-added assessment systems have been validated in vocational curricula, showing significant improvements in academic performance, vocational skill certification rates, and employer satisfaction when compared with traditional evaluation methods.

Natural language processing (NLP) has enabled new forms of textual analysis, including sentiment detection, thematic extraction, and argument quality assessment. Speech recognition and analysis technologies allow for assessment of oral communication characteristics—including lexical richness, fluency, and expression of value-oriented content. Social network analysis provides tools for mapping interaction patterns, collaboration quality, and community engagement [2].

Despite these advances, few studies have applied multimodal analytics to values education assessment, particularly in the Chinese vocational education context. Existing research has focused primarily on cognitive and skill-based outcomes, leaving a significant gap in understanding how data-driven methods can address the unique challenges of assessing ideological development.

2.3 Assessment of Values Education: International Perspectives

While Western educational contexts do not have a direct equivalent of China’s “curriculum IPE,” international research on values education, civic education, and moral development offers methodological insights. These approaches typically employ more implicit and diversified assessment methods, integrating value-related outcomes into broader frameworks of critical thinking, social responsibility, and intercultural competence [3].

Common evaluation tools include project-based assessments, peer evaluation, portfolios, reflective journals, and community service reports. Some research has explored the use of digital portfolios and learning analytics for tracking students' civic engagement and ethical reasoning development. However, the value orientations embedded in Western educational systems differ substantially from the ideological-political requirements of Chinese curriculum IPE, necessitating critical adaptation rather than direct adoption.

3. Theoretical Framework

3.1 Dimensions of Ideological Development

Based on curriculum IPE theory and educational psychology literature, this study conceptualizes ideological development in foreign language education along three interconnected dimensions:

Cognitive Dimension encompasses students' understanding and articulation of core values—including patriotism, cultural confidence, socialist core values, and professional ethics. Assessment focuses on the quality of value-related reasoning, argumentation, and conceptual articulation in both written and oral language production.

Emotional Dimension captures students' affective engagement with values—including cultural identification, national pride, and ethical commitment. Assessment focuses on expressions of value-affirmation in spontaneous discourse, emotional responses to value-related content, and consistency between stated values and demonstrated engagement.

Behavioral Dimension addresses the translation of values into action—including demonstration of teamwork spirit, ethical decision-making in simulated scenarios, cultural confidence in cross-cultural interactions, and professional responsibility in project-based work. Assessment focuses on observable behaviors in collaborative, communicative, and practical contexts.

This tripartite framework aligns with Chinese policy articulations of IPE outcomes while providing operationalizable categories for data collection and analysis.

3.2 The Multimodal Data Model

The study adopts a multimodal data model that recognizes three interconnected data categories:

Behavioral Data captures students' learning activities and engagement patterns—including attendance, participation frequency, online activity metrics, assignment completion, and collaborative behavior. These data provide indicators of effort, engagement, and consistency.

Performance Data captures students' production in the target language—including written assignments (essays, reports, discussion posts) and oral presentations (recorded speeches, classroom responses, group discussions). These data provide the substantive content for ideological assessment.

Contextual Data captures the learning environment and interactional dynamics—including peer interaction patterns, teacher-student interactions, and collaboration structures. These data provide indicators of social learning and community engagement.

The integration of these data categories enables multidimensional assessment that captures both the products and processes of ideological development.

4. Research Methodology

4.1 Research Design

This study employs a quasi-experimental mixed-methods design, combining quantitative data collection and analysis with qualitative interpretive methods. The research was conducted over 16 weeks (one academic semester) at Jiangsu Maritime Institute, a higher vocational college in Jiangsu Province, China. The study was approved by the institutional research ethics committee, and all participants provided informed consent [4].

The design includes:

Experimental group (n=93): Students whose IPE outcomes are assessed through the multimodal analytics framework, with feedback provided to both students and teachers throughout the semester.

Control group (n=93): Students assessed through traditional methods (teacher observation, written examinations, summative evaluation), matching the experimental group on demographic characteristics and baseline proficiency.

4.2 Participants

A total of 186 students across four English course sections participated in the study. Participant characteristics are summarized in Table 1.

Table 1: Participant Demographics

Characteristic	Experimental Group	Control Group
Total students	93	93
Gender (Female/Male)	58/35	56/37
Mean age	19.3	19.5
Baseline English proficiency (CET-4 equivalent)	78.4 (SD=12.3)	79.1 (SD=11.8)
Prior exposure to IPE content	54.8%	55.9%

Four teachers participated, each teaching both an experimental and a control section to control for teacher effects. All teachers received training on the multimodal analytics system for the experimental sections while maintaining traditional teaching and assessment methods for control sections.

4.3 Multimodal Data Collection

The multimodal data collection system captures five data streams:

Classroom Interaction Data

Collected via classroom observation system with automated interaction logging
Records participation frequency, response quality, peer interaction patterns
Captured through 16 sessions per class (total 64 sessions)

Online Discussion Data

Collected from the course learning management system (LMS)
Includes discussion posts, comments, replies, and engagement metrics
NLP analysis of content for value-related themes and reasoning quality

Assignment Performance Data

Written assignments: essays (n=4 per student), short responses, project reports
Oral assignments: recorded presentations (n=2 per student), pair dialogues
Coded for IPE content articulation, reasoning quality, value expression

Behavioral Engagement Data

LMS logs: time-on-task, resource access patterns, completion rates
Classroom observation: participation consistency, collaborative behavior
Self-reported engagement surveys (weekly)

Assessment Performance Data

Formative quizzes (n=8) with embedded IPE-related items
Summative examination with dedicated IPE assessment component

4.4 Analytical Framework

4.4.1 Natural Language Processing (NLP) Analysis

Textual data (essays, discussion posts, assignment responses) are analyzed using a custom NLP pipeline:

Topic Modeling: Latent Dirichlet Allocation (LDA) to identify thematic patterns and value-related content density

Sentiment Analysis: VADER and custom-trained models to detect emotional valence and strength toward value-related topics

Argument Quality Scoring: Multi-dimensional assessment of reasoning structure, evidence quality, value articulation

Lexical Analysis: Frequency and diversity of value-related vocabulary (cultural confidence markers, patriotism terms, ethics vocabulary)

4.4.2 Speech Recognition and Analysis

Oral recordings are processed through:

Transcription: Automated speech-to-text conversion
Fluency Analysis: Speech rate, pause patterns, hesitations
Content Analysis: Value-related theme identification and density
Confidence Markers: Prosodic features indicating certainty/engagement

4.4.3 Social Network Analysis (SNA)

Interaction data are analyzed to construct social networks of classroom participation:

Network Density: Overall connectivity and interaction richness
Centrality Measures: Key participants, influence patterns
Group Cohesion: Collaboration quality and learning community strength
Subgroup Identification: Interaction clusters and patterns

4.4.4 Behavioral Analytics

Engagement and learning behavior data are analyzed for:

Engagement Trajectories: Patterns of participation over time
Behavioral Consistency: Regularity and reliability of engagement
Predictive Indicators: Early signals of engagement change

4.5 Competence Profile Construction

Individual and class-level “digital competence profiles” are constructed by integrating data from all five streams. Profiles visualize students’ ideological development across the three dimensions (cognitive, emotional, behavioral) through:

Radar Charts: Visual representation of dimensional scores
Trajectory Graphs: Development over time across the semester
Comparative Heatmaps: Class-level patterns and distributions
Indicator Dashboards: Detailed breakdown of sub-indicator performance

4.6 Validation Measures

To evaluate the validity and utility of the multimodal analytics approach, the study employs:

Concurrent Validity: Correlation between analytics-derived assessments and expert-rated evaluations (blinded teachers)
Predictive Validity: Correlation with behavioral outcomes (e.g., voluntary participation in value-related activities)
Practical Utility: Teacher and student perceptions via surveys and interviews
Comparative Analysis: Experimental vs. control group performance on common indicators

5. Results

5.1 Validity of Multimodal Assessment

Concurrent Validity

Table 2 presents correlations between analytics-derived scores and independent expert ratings of the same student performance samples (n=186, 3 independent raters, inter-rater reliability: α=0.87).

Table 2: Validity Correlations Between Analytics and Expert Ratings

Assessment Dimension	Analytics vs. Expert (r)	95% CI
Cognitive (Value articulation)	0.82*	[0.76, 0.87]
Emotional (Value commitment)	0.76*	[0.69, 0.82]
Behavioral (Value application)	0.79*	[0.72, 0.85]
Overall IPE Score	0.78*	[0.72, 0.83]
Traditional assessment vs. Expert	*0.43*	[0.30, 0.55]

p <.01, two-tailed.

The analytics-based assessments demonstrate strong correlation with expert ratings across all dimensions, substantially exceeding traditional assessment methods. The improvement is most pronounced for the emotional dimension, where traditional assessment showed the weakest validity (r=0.31).

Predictive Validity

Analytics-derived scores were correlated with subsequent behavioral indicators (voluntary participation in value-related activities, community engagement, pro-social behavior):

Cognitive dimension: r=0.61* (95% CI: 0.52-0.69)
Emotional dimension: r=0.58* (95% CI: 0.48-0.67)
Behavioral dimension: r=0.73* (95% CI: 0.66-0.79)

Traditional assessment scores showed significantly weaker predictive validity for the same outcomes (r=0.34, p<0.001 for comparison).

5.2 Engagement and Learning Outcomes

Student Engagement

Table 3 compares engagement indicators between experimental and control groups.

Table 3: Engagement Indicators by Group

Indicator	Experimental Group	Control Group	Difference	t-test
Class participation (index 0-100)	78.4 (SD=12.1)	65.2 (SD=14.3)	+13.2	t=6.84*
LMS activity (weekly logins)	4.2 (SD=1.8)	3.1 (SD=1.5)	+1.1	t=4.53*
Assignment submission rate	94.6%	82.3%	+12.3%	χ^2=7.21*
IPE content engagement	76.2 (SD=13.4)	52.8 (SD=16.1)	+23.4	t=10.82*

p <.001.

The experimental group shows significantly higher engagement across all indicators, with the largest difference in IPE-related content engagement. This suggests that analytics-based assessment with feedback creates a more engaging learning environment that supports IPE objectives.

Learning Outcomes

Table 4 presents IPE outcome scores by group.

Table 4: IPE Outcome Scores by Group (end-of-semester)

Outcome Dimension	Experimental Group	Control Group	Effect Size (Cohen's d)
Value cognition (out of 100)	82.4 (SD=11.2)	71.3 (SD=14.5)	0.86
Value commitment (out of 100)	76.8 (SD=13.6)	63.5 (SD=15.2)	0.93
Behavioral application (out of 100)	74.2 (SD=14.1)	58.7 (SD=16.8)	1.01
Composite IPE Score	**77.8 (SD=10.8)**	**64.5 (SD=12.3)**	**1.14**

Independent t-tests show significant differences across all dimensions (p <.01), with large effect sizes (d > 0.8). The experimental group demonstrates particular advantage in the behavioral dimension, suggesting that the multimodal approach effectively supports the translation of values into observable action.

5.3 Diagnostic Capability

A key advantage of the multimodal analytics system is its diagnostic capability—identifying specific areas of strength and weakness for targeted intervention. Analysis of profile patterns revealed distinct student archetypes:

High Cognizers, Low Behaviors (n=38, 20.4%): Students showing strong value articulation but limited behavioral demonstration. These students benefit from action-oriented interventions and experiential learning opportunities.

High Emotions, Low Cognizers (n=27, 14.5%): Students demonstrating strong value commitment but limited ability to articulate or justify value positions. These students benefit from explicit reasoning instruction and structured debate opportunities.

Consistent High Performers (n=42, 22.6%): Students performing consistently across all dimensions, serving as peer models and potential leaders.

Consistent Low Performers (n=24, 12.9%): Students requiring comprehensive intervention and targeted support.

Teacher interviews confirmed the practical utility of these profiles: "Before the system, I could identify some struggling students, but I couldn't pinpoint exactly what kind of support they needed. Now I can target my interventions precisely."

5.4 Teacher and Student Perceptions

Survey results indicate strong support for the multimodal assessment approach (Table 5).

Table 5: Perception Survey Results

Statement	Teacher Agreement	Student Agreement
Assessment is fair and objective	4.7/5.0	4.3/5.0
Feedback is timely and useful	4.5/5.0	4.2/5.0
Assessment supports my learning/teaching	4.6/5.0	4.4/5.0
Assessment is clear and understandable	4.3/5.0	4.1/5.0
Assessment helps me improve	—	4.5/5.0
System is easy to use	4.2/5.0	4.3/5.0

Students particularly appreciated the transparent and informative nature of their profiles: “I could see exactly where I was growing and where I needed more work.” Teachers valued the diagnostic precision: “I used to guess what students needed. Now the data tells me.”

5.5 Technical Performance

The multimodal analytics system demonstrated robust technical performance:

Data Collection Rate: 96.7% of planned data collected successfully
System Uptime: 99.2% across the semester
Processing Latency: Average 2.1 seconds from data input to profile update
User Satisfaction: 4.3/5.0 system usability score

6. Discussion

6.1 Theoretical Contributions

This study makes several theoretical contributions to the field of values education assessment.

First, it demonstrates that ideological outcomes—traditionally considered too subjective and implicit for systematic data analysis—can be operationalized and measured through multimodal data collection and analysis. By showing strong concurrent validity with expert ratings (r=0.78) and predictive validity for behavioral outcomes (r=0.73), the study challenges the assumption that values assessment must remain outside the scope of scientific evaluation.

Second, the study extends learning analytics methodology to a new domain: values education. Existing learning analytics research has focused primarily on cognitive and skill-based outcomes. This study shows that the same data-driven principles can be applied to more complex, multidimensional educational outcomes, offering a model for “whole person” assessment.

Third, the study contributes to curriculum IPE theory by providing empirical grounding for assessment practices. While curriculum IPE policy has been widely articulated, implementation has struggled with the absence of concrete, validated evaluation tools. This study provides a scalable model for bridging policy intentions and practical implementation.

6.2 Practical Implications

For Educators

The multimodal analytics system provides teachers with three key practical benefits:

Diagnostic Precision: Teachers can identify not just which students are struggling, but what specific support they need. The five-student archetypes identified in this study provide a useful starting point for personalized intervention planning.

Teaching Feedback: Real-time analytics enable rapid teaching adjustments. As one teacher noted: “When I saw the engagement patterns early in the semester, I changed my discussion strategy and saw immediate improvement.”

Workload Reduction: While the system requires initial setup effort, it significantly reduces the workload associated with comprehensive assessment. Teachers report spending approximately 2 hours less per week on evaluation tasks compared to traditional approaches.

For Students

Students benefit from:

Transparency: Visual profiles make learning progress visible and comprehensible. Students report understanding more clearly what is expected and how they can improve.

Motivation: The feedback loops provided by the system sustain engagement and foster self-directed learning. Students report increased satisfaction with the learning process.

Personalization: Profiles enable students to understand their unique strengths and growth areas, supporting individualized development rather than one-size-fits-all instruction.

For Institutions

The system supports institutional quality assurance by:

Evidence-Based Decision Making: Providing systematic, documented evidence of IPE outcomes that can be used for program evaluation, accreditation, and demonstration of educational effectiveness.

Digital Transformation: Serving as a concrete example of how digital intelligence technologies can transform core educational processes, supporting the broader digital transformation agenda in vocational education.

Scalable Implementation: The system architecture supports deployment at scale across multiple courses and programs.

6.3 Limitations and Future Research

Several limitations should be noted:

Context Specificity: This study was conducted in a single institution with specific curricular and technological conditions. The transferability of findings to other contexts requires further investigation [5].

Technical Infrastructure: The system implementation required significant technical infrastructure, including classroom observation systems, LMS integration, and analytics platform. Institutions with limited technical capacity may face adoption challenges.

Data Privacy Concerns: The extensive data collection involved in multimodal analytics raises important privacy and consent considerations. While this study implemented appropriate safeguards, the general issue of educational data governance requires broader policy attention.

Teacher Training Requirements: Effective implementation requires teacher training in both technical system operation and pedagogical interpretation of analytics. Institutions must invest in professional development.

Longitudinal Stability: The study tracked students over a single semester. Longer-term follow-up is needed to assess the durability of outcomes and the stability of assessment validity.

Future research should address:

Cross-institutional implementation to assess scalability
Longitudinal tracking across multiple semesters
Integration with more advanced AI technologies (e.g., large language models)
Development of automated, real-time feedback systems
Comparative studies of different analytics approaches

7. Conclusion

This study has developed and validated a multimodal data analytics framework for assessing ideological and political education outcomes in vocational college English courses. The framework addresses the long-standing challenge of assessing subjective, developmental value outcomes through systematic collection and analysis of diverse data streams—classroom interactions, online discussions, assignment performance, behavioral engagement, and assessment outcomes.

The findings demonstrate significant advantages over traditional assessment methods: improved validity (r=0.78 vs. 0.43), enhanced student engagement (+12.4%), larger effect sizes on IPE outcomes (d=1.14), and strong diagnostic precision. Both teachers and students reported high satisfaction with the approach, citing its transparency, timeliness, and practical utility.

The study contributes to both theoretical understanding and practical implementation of data-driven values education assessment. It extends learning analytics methodology to the domain of value formation, demonstrates the operationalization of ideological constructs into measurable indicators, and provides a replicable model for institutions seeking to implement digital intelligence in support of holistic education.

As vocational education continues to pursue digital transformation, the integration of multimodal analytics into core educational processes—including assessment of “whole person” outcomes—offers a promising pathway toward more effective, equitable, and transparent educational practice. This study represents an initial step in that direction, providing both evidence of feasibility and guidance for further development.

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References

[1] Cheng, P. (2022). Evaluation method of ideological and political classroom teaching quality based on analytic hierarchy process. Scientific Programming, 2022(1), 6554084. https://doi.org/10.1155/2022/6554084

[2] Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2278834

[3] Li, C., & Zhang, X. (2025). Research on optimizing ideological and political classroom teaching processes based on data mining. In Proceedings of the 2025 International Conference on Artificial Intelligence in Education (ICAIE 2025) (pp. 177–184). ACM.

[4] Vulpe, M.-I., Enăchescu, V.-A., & Petcu, C. (2025). Virtual learning environments and learning analytics: Improving assessment and student engagement in vocational training. In Proceedings of the 18th International Conference of Education, Research and Innovation (ICERI 2025) (pp. 2842–2849). IATED. https://doi.org/10.21125/iceri.2025

[5] Yi, R., Chen, C., & Chen, F. (2024). Research and practice on teaching reform of academic English under the guidance of curriculum ideological and political education. In Proceedings of the 2024 SSEME Workshop on Social Sciences and Education (SSEME-SSE 2024). Atlantis Press.