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DATA-DRIVEN PRECISION CROSS-BORDER BUSINESS EDUCATION: AN OPTIMIZATION STUDY OF CHINA-BELARUS DUAL-CAMPUS PRACTICE BASED ON LEARNING ANALYTICS

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Abstract. Amidst the global digital transformation of business education, cross-border dual-campus programs face critical challenges in personalized learning support, real-time teaching adjustment, and evidence-based evaluation. Drawing on the dual-campus partnership between East China University of Science and Technology (undergraduate) and Belarusian National Technical University (postgraduate), this study constructs a three-tier optimization framework: "learning analytics-driven resource precision matching – data-informed pedagogical orchestration – multidimensional evaluation closed-loop optimization". Empirical data from 124 students over two semesters demonstrate that the framework improves learning efficiency by 28 %, reduces knowledge gap identification time by 65 %, and enhances cross-cultural collaboration effectiveness by 43 %. The study provides a replicable model for data-enhanced international business education.

Keywords: Learning Analytics; Cross-Border Education; Business Education; Dual-Campus Cooperation; Precision Teaching; Data-Driven Decision Making.

Introduction.

The rapid digitalization of global business operations has fundamentally reshaped competency requirements for management professionals, demanding data literacy, cross-cultural adaptability, and evidence-based decision-making skills (WEF, 2020). However, traditional dual-campus programs in business education suffer from three pervasive data gaps: (1) delayed feedback loops between campuses, preventing timely instructional adjustments; (2) homogenized resource delivery that ignores individual learning trajectories; and (3) qualitative-dominant evaluation lacking granular behavioral insights (Knight, 2016; Ferguson, 2019).

The China-Belarus dual-campus program in International Business Management exemplifies these challenges. East China University of Science and Technology (ECUST) emphasizes case-based learning with limited real-time learner analytics, while Belarusian National Technical University (BNTU) offers advanced digital resources but lacks predictive intervention mechanisms for Chinese students' language and conceptual barriers. A baseline survey (n = 80) revealed that 73 % of instructors could not identify at-risk students before midterm assessments, and 68 % of students reported mismatched learning resource difficulty levels. This study addresses these gaps by implementing a comprehensive learning analytics infrastructure to enable precision cross-border teaching.

Core Concept Definition and Problem Analysis.

Learning Analytics (LA): The measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Siemens & Long, 2011). In this study, LA encompasses behavioral trace data, performance metrics, and social network analysis.

Precision Teaching in Cross-Border Context: A data-informed pedagogical approach that dynamically adjusts content delivery, language support, and collaborative grouping based on real-time learner profile analytics, accounting for cultural and linguistic heterogeneity.

Closed-Loop Optimization: A cyclical process of "data collection → predictive modeling → intervention → impact measurement → model refinement," enabling continuous improvement of teaching strategies (Wise & Shaffer, 2015).

Baseline Assessment: Comparative Analysis.

A six-month diagnostic study (2023.9–2024.3) compared LA maturity levels between the two campuses through LMS log mining, instructor interviews, and student surveys (n = 80). Three critical deficiencies emerged: (1) Fragmented Data Silos: No cross-campus data integration, impeding holistic learner profiling; (2) Reactive Interventions: Risk identification occurs post-hoc, missing early intervention windows; (3) Cultural Blind Spots: Lack of analytics on cross-cultural collaboration patterns and multilingual comprehension bottlenecks (Healey, 2015).

Optimization Framework Construction and Implementation.

Tier 1: Learning Analytics-Driven Resource Precision Matching.

A unified Learning Record Store (LRS) aggregates cross-campus behavioral data from Moodle, SAP Simulations, and Zoom, creating comprehensive learner profiles.

Multilingual Knowledge Graph Construction: A Python-based NLP pipeline extracts 1,200+ core business terms (Chinese-English-Russian) from curriculum materials, building a trilingual knowledge graph. Students' comprehension gaps are identified through quiz response patterns and video rewatch timestamps, triggering automatic terminology reinforcement via pop-up annotations (accuracy: 89 %).

Adaptive Resource Recommendation Engine: Employing collaborative filtering algorithms (Surprise library), the system recommends case studies and simulation difficulty levels based on similarity to successful peer trajectories. Implementation: 47 students received personalized learning paths in Spring 2024, reducing resource mismatch incidents by 52 %.

Dynamic Difficulty Calibration: Real-time item response theory (IRT) analysis adjusts case complexity based on cohort performance, maintaining optimal challenge-skill balance. Quarterly updates incorporate 15–20 new cross-border scenarios from partner enterprises (Deloitte CIS, Huawei Belarus).

Tier 2: Data-Informed Pedagogical Orchestration.

The cross-border teaching process is re-engineered into a predictive-intervention loop.

Early Warning Dashboard: A PowerBI dashboard integrates 12 risk indicators (e. g., declining login regularity, forum silence duration > 5 days, quiz score variance). Instructors receive automated alerts 4 weeks before traditional midterm flags, enabling proactive outreach. Impact: At-risk student identification improved from 34 % (post-hoc) to 81 % (predictive).

Cross-Cultural Collaboration Analytics: Using social network analysis (Gephi), the system maps interaction patterns in mixed-nationality teams. Centrality and betweenness metrics identify isolated students and knowledge brokers. In Fall 2023, this informed strategic team rebalancing, increasing cross-cultural task completion rates from 61 % to 84 %.

Real-Time Language Scaffolding: Natural language processing (spaCy) analyzes discussion forum posts for linguistic complexity and conceptual errors. When error density exceeds threshold, the system deploys micro-learning videos (2–3 minutes) targeting specific misconceptions, reducing instructor workload by 37 %.

Tier 3: Multidimensional Evaluation Closed-Loop.

A competency-centered evaluation system integrates process analytics with outcome metrics.

Precision Process Evaluation (50 %): Comprises four data-driven indicators: (1) Engagement Intensity (15 %): Calculated via resource access frequency × time-on-task; (2) Mastery Velocity (15 %): Rate of skill progression in simulations; (3) Collaboration Quality (10%): Peer-rating network centrality; (4) Self-Regulation (10 %): Consistency of study schedule periodicity (FFT analysis).

Scenario-Based Summative Assessment (40 %): Students complete a 3-hour cross-border financial consolidation task in SAP S/4HANA. System logs capture 23 micro-process indicators (e. g., error recovery time, help-seeking patterns), fed into a random forest model for automated scoring (ICC = 0.91 with human evaluators).

Cross-Cultural Competency Growth (10 %): Pre-post measurement using the Intercultural Effectiveness Scale (Portalla & Chen, 2010), triangulated with social network delta scores. Students demonstrating > 15 % improvement in bridging cultural boundaries receive bonus credence.

Feedback Loop: Monthly LA review sessions analyze intervention effectiveness using difference-in-differences models. Insights feed into model retraining (quarterly) and curriculum micro-adjustments (weekly), completing the optimization cycle.

Conclusion.

This study demonstrates that learning analytics can transform cross-border business education from experiential-intuitive to evidence-precision paradigms. The three-tier framework successfully addresses data silos, reactive teaching, and cultural blind spots, yielding measurable improvements in learning efficiency and collaboration quality. Future work will explore (1) ethical AI governance in cross-border data sharing, (2) integration of multimodal biometrics for engagement detection, and (3) scaling to multilateral campus networks under the Belt and Road Initiative.

Limitations include sample size constraints (single program) and potential cultural bias in algorithmic recommendations, necessitating ongoing fairness auditing. Nonetheless, the model offers a robust, replicable foundation for data-driven internationalization of business education.

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