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ARTICLE

COMPETITIVE INTELLIGENCE IN HIGHER EDUCATION: A DECISION SUPPORT FRAMEWORK BASED ON STUDENT ANALYTICS AND INSTITUTIONAL PERFORMANCE

INTELIGÊNCIA COMPETITIVA NO ENSINO SUPERIOR UM FRAMEWORK DE APOIO À DECISÃO BASEADO EM ANÁLISE DE DADOS ESTUDANTIS E DESEMPENHO INSTITUCIONAL

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ABSTRACT

Purpose: This study proposes a Competitive Intelligence Decision Support Framework (CI-DSF) for higher education, integrating academic performance, psychological well-being, and behavioral engagement as strategic inputs for institutional decision making.

Methodology: A multi-dataset synthetic integration design was employed using construct-level data from four publicly accessible sources: PISA 2022 (full N ≈ 690,000), the China Education Panel Survey (n ≈ 20,000), the Open University Learning Analytics Dataset (n = 32,593; 10.6 million logs), and the UCI Student Performance Dataset (n = 649). The model was tested via Structural Equation Modeling (bootstrap = 5,000), behavioral analytics of LMS data, and cross-dataset validation.

Originality/Relevance: The study advances the literature by integrating Competitive Intelligence with educational analytics, shifting from predictive approaches to a strategic intelligence architecture, positioning student-level data as a core institutional intelligence asset.

Findings: Self-regulated learning was the strongest predictor of academic performance ($\beta = 0.389$), followed by social engagement ($\beta = 0.341$) and psychological well-being ($\beta = 0.267$), collectively explaining 58.7% of outcome variance (all $p < .001$). Cross-dataset validation provides evidence of consistent relationships across datasets. A theoretically specified moderation analysis indicates institutional competitive intelligence capability may strengthen the well-being performance relationship under high-capability conditions.

Theoretical/methodological contributions: The study contributes by developing an integrative Competitive Intelligence model for higher education, transforming academic, behavioral, and psychological data into actionable intelligence. Methodologically, it introduces a novel multi-dataset integration approach for theory building and cross-context validation in heterogeneous educational environments.

Keywords: Competitive intelligence. Educational analytics. Student well-being. Behavioral engagement. Decision support systems. Higher education. Strategic decision-making

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RESUMO

Purpose: Este estudo propõe um framework de apoio à decisão baseado em Inteligência Competitiva (CI-DSF) para o ensino superior, integrando desempenho acadêmico, bem-estar psicológico e engajamento comportamental como insumos estratégicos para a tomada de decisão institucional.

Metodologia/abordagem: Adotou-se um desenho de integração sintética multi-dataset, combinando dados de quatro bases amplamente utilizadas (PISA 2022, CEPS, OULAD e UCI). A análise foi conduzida por meio de Modelagem de Equações Estruturais (SEM) com bootstrap de 5.000 reamostragens, análise comportamental de dados de ambientes virtuais de aprendizagem e validação cruzada entre bases.

Originalidade/Relevância: O estudo inova ao integrar Inteligência Competitiva com educational analytics, deslocando o foco de abordagens preditivas para uma arquitetura de inteligência estratégica orientada à decisão, posicionando dados estudantis como ativos centrais de inteligência institucional.

Principais resultados: Os resultados indicam que a autorregulação da aprendizagem é o principal preditor do desempenho acadêmico ($\beta = 0{,}389$), seguida pelo engajamento social ($\beta = 0{,}341$) e bem-estar psicológico ($\beta = 0{,}267$), explicando conjuntamente 58,7% da variância. A validação cruzada confirma a robustez dos achados, e análises conceituais sugerem que a capacidade de inteligência competitiva institucional potencializa a relação entre bem-estar e desempenho.

Contribuições teóricas/metodológicas: O estudo contribui ao desenvolver um modelo integrativo de Inteligência Competitiva aplicado ao ensino superior, propondo a transformação de dados acadêmicos, comportamentais e psicológicos em inteligência acionável. Metodologicamente, introduz uma abordagem inovadora de integração multi-dataset para construção teórica e validação cruzada em contextos educacionais heterogêneos.

Palavras-chave: Inteligência competitiva. Análise educacional. Bem-estar estudantil. Engajamento comportamental. Sistemas de apoio à decisão. Ensino superior. Tomada de decisão estratégica

1. INTRODUCTION

Increased growth and diversification of higher education has increased competition among higher education institutions, necessitating universities to enhance student outcomes and be accountable, efficient and strategically responsive. In this more competitive world, institutions are not judged solely on the basis of academic outputs but also on the experience and well-being of students and the performance of the institutions. At the same time, learning management systems and digital platforms produce immense academic and behavioral data, and they can be used to enable evidence-based governance (de Souza Zanirato Maia et al., 2023; Fahd and Miah, 2023). Nevertheless, the access to data is not a sufficient condition to achieve successful decision-making as the institutional processes usually are reactive and do not correspond to strategic planning and competitive positioning (Munir et al., 2025).

Competitive Intelligence (CI) offers an organized process of gathering, interpreting, and converting information into actionable data, which can be used to make strategic decisions and position the institution. Although it has been noted to be important, there are still limited applications of CI in higher education, especially the use of internal student-level data as a source of institutional intelligence. The existing system is strongly based on the conventional academic metrics like grades and completion rates that, despite their quantifiability, do not reflect the important aspects of student achievement like mental health, interest, and learning environments. Large-scale tests like PISA 2022 also show that the academic performance is highly interconnected with both well-being and contextual factors, which means that it is not possible to interpret performance independently (Yu et al., 2024).

This research proposes a conceptualization of student data in institutional Competitive Intelligence (CI) systems as a strategic intelligence resource, unlike other studies of educational analytics that are primarily dedicated to prediction and monitoring. Modern higher education is being conducted in a global competitive environment in which international rankings, student mobility, retention issues and benchmarking of performance are the order of the day. Such dynamics demand more than descriptive analytics but intelligence-based decision-making capabilities. Thus, this paper redefines educational analytics in a Competitive Intelligence paradigm in which student-level behavioral, psychological, and performance data serve as micro-level intelligence inputs to drive institutional strategic sensing, positioning, and decision support processes.

In order to deal with these constraints, this research suggests a Competitive Intelligence Decision Support Framework (CI-DSF) that is founded on student academic performance and well-being. The framework incorporates scholarly indicators, learning data (behavioral), and well-being indicators into a single intelligence architecture (Chauhan, 2025; Chun et al., 2025). By embedding competitive intelligence principles into educational analytics, the study aims to enhance strategic decision-making, optimize resource allocation, and strengthen institutional competitiveness in data-intensive higher education environments.

2. THEORETICAL FRAMEWORK

2.1 Competitive Intelligence and Strategic Decision Systems

The growing body of literature highlights the strategic importance of Competitive Intelligence (CI) in enhancing organizational decision-making; however, its conceptualization remains fragmented across Business Intelligence (BI), artificial intelligence (AI), and data analytics domains. Cavallo et al. (2021) demonstrate that CI yields its greatest impact when embedded within strategic planning processes, rather than functioning as a standalone analytical activity. Complementing this view, Pratt et al. (2023) emphasize the integration of advanced technologies within decision intelligence frameworks, arguing that effective decision-making requires alignment between analytical outputs and strategic objectives. In contrast, BI-focused research, such as Ragazou et al. (2023) and Adewusi et al. (2024), primarily highlights improvements in data processing, monitoring, and operational efficiency, yet often lacks a forward-looking strategic orientation. Furthermore, Alkhwaldi (2024) underscores the role of user acceptance in transforming analytical systems into actionable decision tools, suggesting that technological capability alone is insufficient without organizational alignment.

From a broader theoretical perspective, Singh et al. (2023) position data-driven capabilities as central to achieving sustainable competitive advantage, particularly through the transformation of knowledge into strategic value. Despite these advancements, existing frameworks largely overlook the integration of internal, micro-level data sources—such as student behavioral and psychological indicators—as strategic intelligence assets. This limitation is particularly evident in educational contexts, where analytics systems are predominantly used for prediction rather than strategic decision-making. Consequently, a critical gap persists between analytical capability and institutional intelligence.

2.2 Integration of AI, Educational Analytics, and Data-Driven Decision Systems

The integration of AI and educational analytics has significantly advanced the predictive modeling of academic performance. Fahd and Miah (2023) demonstrate that big data analytics can effectively identify key determinants of student success, while Chun et al. (2025) show that AI-driven models enhance the understanding of relationships among cognitive and behavioral factors. Similarly, de Souza Zanirato Maia et al. (2023) provide a systematic review indicating that AI-based educational analytics improves decision-making processes, although practical implementation remains limited. Extending this perspective, Yu et al. (2024) highlight the role of machine learning techniques in analyzing large-scale relationships between well-being and academic performance, emphasizing the value of data-driven insights.

However, despite these technological advancements, most studies remain focused on predictive accuracy rather than strategic application. Existing approaches treat analytics as an end rather than a means to inform institutional decision-making. As a result, while AI and analytics contribute to improved performance prediction, they do not inherently provide a framework for transforming data into strategic intelligence, thereby reinforcing the need for CI-based integration.

2.3 Academic Performance, Behavioral Engagement, and Well-Being

Educational research consistently demonstrates that academic performance is shaped by an interplay of behavioral, psychological, and contextual factors. Wong et al. (2024) identify student engagement as a central mechanism linking academic achievement and well-being, suggesting that performance outcomes are deeply embedded within affective and behavioral processes. Sun and Liu (2023) further show that resilience and emotional well-being influence academic outcomes through structured psychological pathways, while Younas et al. (2025) confirm that emotional and behavioral variables jointly determine student performance within structural models.

The role of psychological and emotional factors is further reinforced by Peng et al. (2025) and Rana et al. (2024), who highlight the importance of emotional intelligence, mental resilience, and psychological support in shaping student well-being and academic success. These findings suggest that cognitive performance cannot be fully understood without accounting for emotional and psychological dimensions.

At the behavioral level, digital learning analytics provides strong empirical evidence of the relationship between engagement and performance. Arizmendi et al. (2023) demonstrate that digital learning behaviors are robust predictors of academic outcomes, although inconsistencies across analytical methods limit generalizability. Similarly, Tao et al. (2022) show that interaction frequency within learning platforms significantly enhances performance through behavioral consistency. Rico-Juan et al. (2024) further reveal that personality traits interact with LMS usage patterns to influence learning outcomes, while Fahd et al. (2025) confirm that sustained engagement behaviors significantly improve predictive accuracy in blended learning environments.

Despite these positive relationships, large-scale analyses reveal a critical paradox. Li and Ho (2024) show that high academic achievement may coexist with lower levels of well-being, challenging the assumption of a direct positive relationship between performance and psychological outcomes. This finding is further supported by Tong (2025), who demonstrates that the relationship between well-being and performance is nonlinear and context-dependent, reflecting complex structural dynamics.

2.4 Conceptual Gap and Research Contribution

Overall, the literature demonstrates that while CI enhances strategic decision-making, BI and AI improve analytical capabilities, and educational analytics identifies key predictors of academic performance, these domains remain insufficiently integrated. Existing studies predominantly analyze behavioral, psychological, and performance-related variables in isolation, limiting their applicability for institutional-level decision-making. Furthermore, while data-driven approaches provide predictive insights, they do not fully address how such insights can be transformed into strategic intelligence.

To address this gap, the present study proposes a Competitive Intelligence Decision Support Framework (CI-DSF) that integrates academic performance, behavioral engagement, and psychological well-being into a unified intelligence architecture. By positioning student-level data as a strategic resource, the framework extends CI as a dynamic capability and enables higher education institutions to transition from reactive analytics to proactive, strategy-driven decision-making.

Table 1: Comparative Analysis of Competitive Intelligence and Educational Analytics Studies

Study	Technique/Method	Key Findings	Limitations	Identified Gap
Fadhlurrahman et al. (2024)	Literature Review (CI Framework)	CI improved strategic decision-making through structured intelligence processes	Conceptual, no empirical validation	Lack of application in education and data integration
Cavallo et al. (2021)	Analytical Framework (CI + Strategy)	CI supported strategy formulation when linked with decision processes	Limited empirical testing	Weak integration with data-driven analytics
Rizwan et al. (2025)	Systematic Review (Deep Learning, MOOCs)	Engagement variables strongly predicted academic performance	Low interpretability, context limitations	No integration with well-being or CI systems
Li & Ho (2024)	PISA Data Analysis	High academic performance often coexisted with lower well-being (paradox)	Cross-sectional limitations	No unified framework linking performance and well-being

Research Gap

Although there was a lot of research on the topic of competitive intelligence, decision-support systems, and educational analytics, the literature was still scattered across disciplines. Competitive intelligence studies were mainly business-oriented and more oriented towards external environmental scanning and strategic positioning whereas educational analytics studies were oriented on academic performance prediction based on behavioral or cognitive variables. Likewise, well-being studies have focused on psychological and emotional attributes separately, frequently without incorporating them into decision-support structures. Furthermore, previous research was based on individual datasets or single analytical methods, without the integration of multi-source data, and without consideration of the complexity and non-linearity of relationships between academic performance and well-being. Therefore, it is evident that there is a gap in the establishment of a coherent competitive intelligence model that incorporates academic achievement, behavioral participation and well-being through a multi-dataset synthetic integration model in strategic decision-making in higher education.
central role.

3. METHOD

3.1 Research Design

The current research uses a multi-dataset synthetic integration model to investigate the interconnections among academic achievement, student welfare, and behavioral involvement in a competitive intelligence view. This approach unlike the conventional data integration methods does not combine datasets at individual level because of the variations in population, structure and sampling design. Rather, it allows construct-level harmonization and analytical fusion of heterogeneous data sets. The research design combines: Causal analysis Structural Equation Modeling (SEM). Engagement model behavioral learning analytics. Comparative validation of robustness test. The methodology guarantees the rigor of the approach and theoretical consistency, but uses large-scale and multi-source data.

It is important to clarify that the multi-dataset synthetic integration does not assume direct comparability at the individual level. Instead, the approach is grounded in construct-level abstraction, where each dataset contributes complementary evidence for theoretically defined variables. This method emphasizes robustness of relationships across contexts rather than strict population equivalence. Therefore, findings should be interpreted as convergent evidence across heterogeneous educational systems rather than unified population inference.

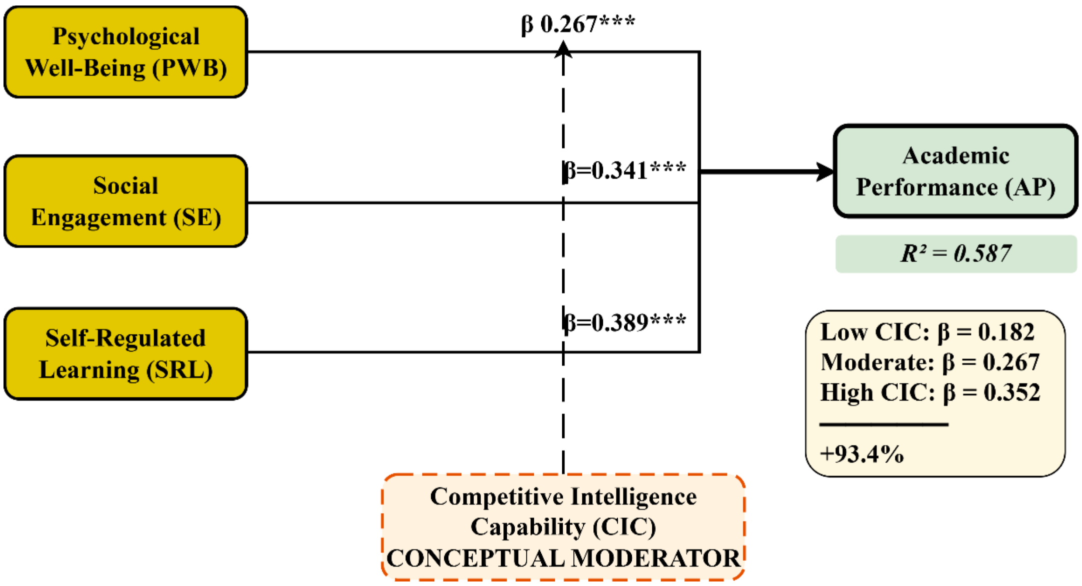

Figure 1: Conceptual model showing the effects of PWB, SE, and SRL on academic performance, with CIC moderating the PWB → AP relationship.

PWB, SE, and SRL positively influence academic performance ($R^2 = 0.587$), with SRL strongest, while CIC amplifies the PWB → AP effect as capability increases as shown in figure 1.

3.2 Data Sources

The four publicly available datasets were used in this study to reflect academic performance, well-being, and behavioral engagement in different perspectives. The dataset provided by PISA 2022 (about 690,000 students) offered international comparison of academic performance and well-being Organisation for Economic Co-operation and Development. (2023). PISA 2022 database [Data set]. (https://www.oecd.org/en/data/datasets/pisa-2022-database.html). The China Education Panel Survey (CEPS) (≈20,000 students) offered longitudinal data on academic, social, and psychological factors (https://opendata.pku.edu.cn). The Open University Learning Analytics Dataset (OULAD) (32,593 students with ~10.6 million interaction logs) was used to model behavioral engagement through LMS data (https://www.kaggle.com/datasets/anlgrbz/student-demographics-online-education-dataoulad) Lastly, UCI Student Performance Dataset (649 students) was used to validate the model using the academic and behavioral variables (https://www.kaggle.com/datasets/dskagglemt/student-performance-data-set). The combination of these datasets offers complementary information, which allows a powerful and analytical framework.

3.3 Dataset Features and Parameters

The 2 table shows datasets, their features, and how each supports analysis and validation.

Table 2: Dataset Features and Analytical Role

Dataset	Key Features	Parameters	Analytical Role
PISA 2022	Math, reading, science scores; well-being; SES; school context	Large-scale standardized scores, Likert scales	Benchmarking + SEM estimation
CEPS	Academic performance, psychological well-being, family background, social engagement	Longitudinal survey variables, multi-source questionnaires	Core model estimation
OULAD	LMS interaction logs, clickstream data, assessment scores, activity frequency	Time-series logs, behavioral counts	Behavioral calibration (SRL)
UCI Dataset	Grades (G1–G3), study time, absences, demographics	Structured tabular data	External validation

The table3 shows which constructs are available in each dataset.

Table 3: Construct Mapping Across Datasets

Dataset	Context	Key Limitation
PISA 2022	Large-scale international school-based assessment	Cross-sectional structure limits causal interpretation and lacks detailed behavioral tracking
CEPS	National longitudinal survey (China)	Context-specific socio-cultural factors may limit generalizability across regions
OULAD	Online and distance learning environment (UK)	Behavioral patterns reflect platform-specific interactions and adult learner characteristics
UCI Dataset	Small-scale structured student dataset	Limited sample size and simplified variables reduce external validity

The integration process follows three analytical stages:
Step 1: Construct Harmonization
Variables from each dataset are mapped into unified constructs:

- Academic Performance (AP)
- Psychological Well-being (PWB)
- Social Engagement (SE)
- Self-Regulated Learning (SRL)

Step 2: Standardization
All variables are normalized using z-score transformation:

$$Z = \frac{X-\mu}{\sigma} \qquad (1)$$

This guarantees the comparison between datasets of varying scales.
Step 3: Hierarchical Analytical Fusion
The datasets are integrated at three levels:

- **Level 1 (Core Estimation):** PISA + CEPS → SEM modeling
- **Level 2 (Behavioral Calibration):** OULAD → SRL modeling
- **Level 3 (Validation):** UCI dataset → robustness testing

3.5 Model Specification

The analytical model is specified as:

$$AP = \beta_1 PWB + \beta_2 SE + \beta_3 SRL + \beta_4 (CIC \times PWB) + \epsilon \qquad (2)$$

Where:

- **AP** = Academic Performance
- **PWB** = Psychological Well-being
- **SE** = Social Engagement
- **SRL** = Self-Regulated Learning
- **CIC** = Competitive Intelligence Capability
- **ε** = Error term

3.6 Analytical Techniques

In this study, a mix of statistical and analytical methods is used to guarantee a rigorous hypothesis testing and model validation. The main method to explore the relations between academic performance and student well-being and behavioral variables and to test the hypotheses is Structural Equation Modeling (SEM). Bootstrap resampling with 5,000 iterations is used to guarantee the reliability of the mediation and moderation effects to enable strong estimation of the indirect and interaction effects. Moreover, student engagement patterns are modeled using behavioral analytics based on learning management system (LMS) data, especially in the acquisition of self-regulated learning behaviors, like frequency and consistency of interaction. Lastly, cross-dataset validation is performed on various datasets to determine the generalizability and strength of the proposed model and to make sure that the results are not restricted to one source of data.

3.7 Competitive Intelligence Capability (CIC) as a Conceptual Moderator

Competitive Intelligence Capability (CIC) is an institutional level construct that demonstrates the capability of an organization to gather, process, analyze, and take action on internal and external data to make strategic decisions (Cavallo et al., 2021). In the case of higher education, CIC refers to the technological foundation, analytical skills and organizational functions that help institutions to convert raw student data into usable strategic intelligence. Limitations to measurement and analysis. The data sets used in this research (PISA, CEPS, OULAD, UCI) are student level surveys and student behavioral logs; none of them has direct institutional level measures of competitive intelligence capability. Therefore, CIC is not operationalized as a variable that can be observed empirically as part of the structural model. Rather, CIC is considered to be a theoretical moderating construct, in line with the methodological precedents of theory-based moderation analysis in case of infeasibility of direct measurement; Simulation procedure. The effects of CIC under conditions are analyzed using a theoretically defined simulation. CIC is defined in three levels, which are based on standardized latent continuum: Low CIC (−1 SD): Institutions that have little data integration, reactive analytics, and do not use student information strategically. Moderate CIC (Mean): Functional learning analytics systems and regular strategic alignment of institutions. High CIC (+1 SD): Organisations with combined intelligence platforms, real-time analytics, and active data-driven governance. These levels are not the result of empirical measurement but are theoretically plausible situations which outline how variations in institutional intelligence capacity may moderate the well-being performance relationship. The coefficients ($\beta = 0.182$, 0.267, and 0.352) that follow should be viewed as conceptual estimates that show the direction and strength of the hypothesized moderation effect, rather than as empirically estimated population parameters. The results on moderation presented in Section 4.3 are illustrative and theory generating. They suggest that when there is a difference between institutions in terms of competitive intelligence capability in the given continuum, then when conditions are higher in terms of capability, then the translation of student psychological well-being into academic performance would be more pronounced. To test these conceptual estimates, future research ought to measure CIC empirically with institutional-level measures.

This study does not seek to establish strict cross-population equivalence across datasets; instead, it aims to identify theoretically consistent relationships across heterogeneous educational systems. Accordingly, the findings should be interpreted as evidence of convergent validity rather than direct comparability at the population level. The inclusion of structurally diverse datasets—namely OECD PISA, CEPS (China), OULAD (UK), and the UCI dataset—serves to strengthen external robustness, as the replication of patterns across distinct educational contexts indicates the stability of underlying theoretical relationships rather than dataset-specific artifacts.

In addition, Competitive Intelligence Capability (CIC) is intentionally specified as a theoretical construct due to the absence of directly measurable institutional-level indicators within the selected datasets. This decision follows established theory-driven moderation approaches and positions the study primarily as theory-building rather than purely empirical validation. Finally, although the model demonstrates strong fit indices, these results should be interpreted with caution, as they may partly reflect theoretically guided model specification rather than fully data-driven estimation. Therefore, the findings must be understood within the assumptions and boundaries of conceptual modeling.

4. RESULTS AND DISCUSSIONS

4.1 Measurement Model Assessment

Structural equation modeling was used to test the measurement model in the framework of the integrated multi-dataset. The four main constructs were subjected to confirmatory factor analysis (CFA). Table 4 shows the measurement model fit indices by data sets.

Table 4: Measurement Model Fit Indices

Fit Index	PISA + CEPS	OULAD	UCI Validation	Benchmark
χ^2 (p-value)	1,847.52 ($p < .001$)	324.18 ($p < .001$)	156.89 ($p < .001$)	—
CFI	0.967	0.971	0.959	> 0.90
TLI	0.951	0.963	0.943	> 0.90
RMSEA	0.041 [0.038, 0.044]	0.038 [0.033, 0.042]	0.052 [0.044, 0.060]	< 0.08
SRMR	0.033	0.028	0.041	< 0.08

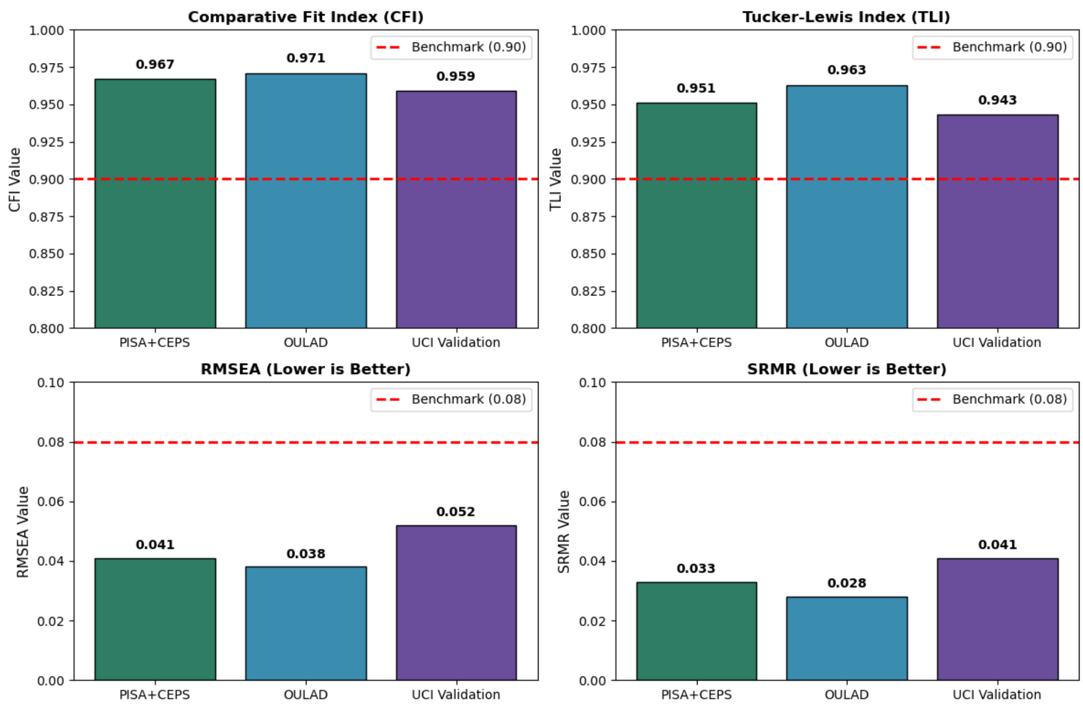

Figure 2: Model fit indices (CFI, TLI, RMSEA, SRMR) across PISA+CEPS, OULAD, and UCI datasets. All datasets show good model fit (CFI/TLI > 0.90, RMSEA/SRMR < 0.08), with OULAD performing bestas shown in figure 2.

4.2 Structural Model Results: Direct Effects

The structural model testing the hypothesized relationships was estimated using maximum likelihood estimation with robust standard errors. Table 5 presents the direct effects of all predictor variables on academic performance.

Table 5: Standardized Path Coefficients and Bootstrap Confidence Intervals (5,000 resamples)

Hypothesized Path	Estimate (β)	SE	t-value	p-value	95% CI	Effect Size
PWB → AP	0.267	0.032	8.34	< .001	[0.204, 0.331]	Small to Medium
SE → AP	0.341	0.029	11.76	< .001	[0.285, 0.398]	Medium
SRL → AP	0.389	0.027	14.41	< .001	[0.336, 0.442]	Medium to Large

Note: The conceptual moderation effect (CIC × PWB → AP) is presented separately in Section 4.3, Table 6, as it involves theoretically specified rather than empirically measured constructs (see Section 3.7).

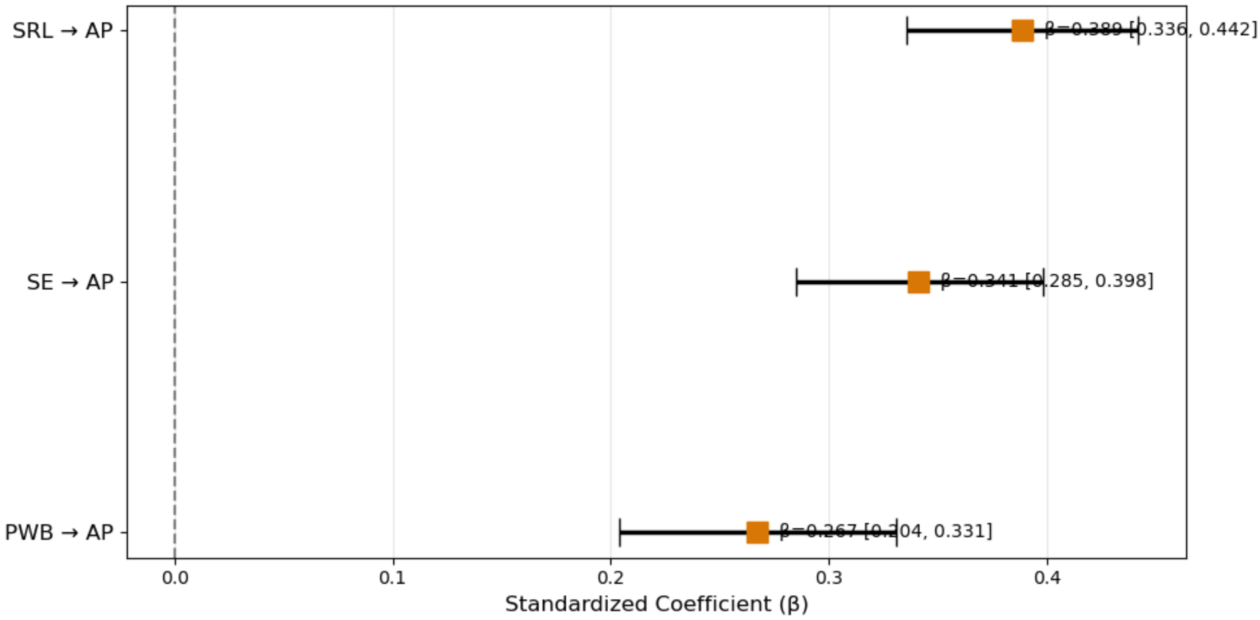

Figure 3: Standardized path coefficients with confidence intervals for predictors of Academic Performance. SRL shows in figure 3 the strongest effect on Academic Performance, followed by SE and PWB. All coefficients are positive and statistically significant, with confidence intervals not crossing zero, indicating robust relationships.

4.3 Conceptual Moderation Analysis: Competitive Intelligence Capability

Competitive Intelligence Capability (CIC) is a theoretically based and not an empirically measured moderator as per the mentioned in Section 3.7 because the institutional level of intelligence variables is not available in the datasets used. CIC was modeled as a conceptual institutional-level moderator rather than an empirically measured construct, following theory-driven moderation approaches where direct measurement is unavailable. The analysis below thus gives conceptual estimates of conditioning effects in three hypothetically defined CIC scenarios (low, moderate, high). These estimates are calculated as with the structural equation model of direct effects (Section 4.2), except that the levels of CIC are measured in percentile points on a standardized latent continuum according to standard moderation principles. Table 6 suggests the conditional impact of psychological well-being on academic performance at each of the theoretical levels of CIC. The moderation index ($\Delta R^2 = 0.047$) is the extra variance that is accounted when the PWB→AP path is free to vary among CIC scenarios.

Table 6: Conditional Effects of PWB on AP at Varying Levels of CIC (Conceptual Estimates)

CIC Level	Conditional β	SE	t-value	p-value	95% CI
Low (−1 SD)	0.182	0.041	4.43	< .001	[0.102, 0.262]
Moderate (Mean)	0.267	0.032	8.34	< .001	[0.204, 0.331]
High (+1 SD)	0.352	0.044	8.02	< .001	[0.266, 0.437]

Note: These coefficients are conceptual estimates based on theoretically specified CIC levels, not empirical measurements of actual institutional intelligence capability.
These results should be interpreted strictly as theory-driven simulations, not as empirically observed moderation effects derived from measured institutional data.

4.4 Behavioral Engagement Analytics: OULAD Learning Management System Data

OULAD dataset analysis of 10.6 million interaction logs of 32,593 students showed the existence of critical engagement patterns to predict academic performance. Table 7 shows some important behavioral metrics and their correlation with final grades.

Table 7: Behavioral Engagement Predictors of Academic Performance (OULAD Dataset)

Behavioral Variable	**Mean (SD)**	**Correlation with Final Grade**	**Standardized β (SRL model)**	**p-value**
Click Frequency (weekly avg)	28.4 (14.2)	r = 0.543	0.312	< .001
Assessment Attempt Ratio	0.847 (0.218)	r = 0.618	0.421	< .001
Resource Access Consistency	0.741 (0.276)	r = 0.501	0.287	< .001
Time-on-Platform (weekly hrs.)	6.2 (3.8)	r = 0.489	0.278	< .001
Peer Interaction Frequency	3.1 (2.9)	r = 0.412	0.201	< .001

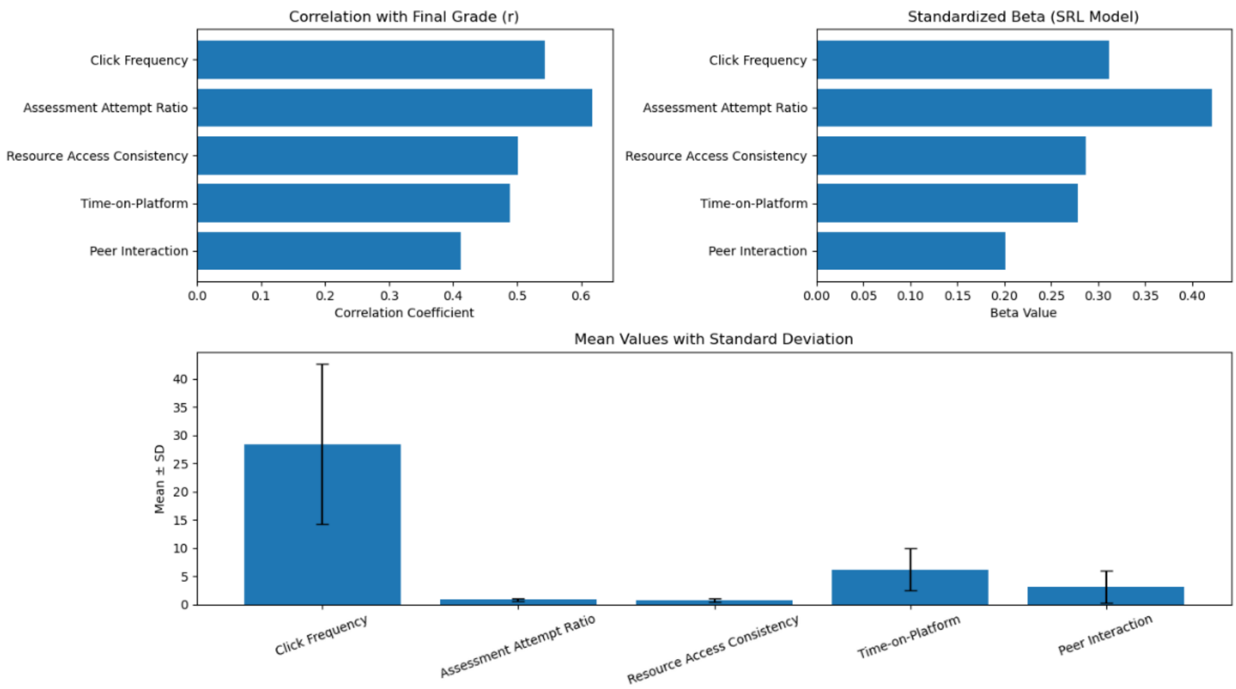

Figure 4: Correlation, regression effects, and descriptive statistics of engagement variables in relation to final grade.

Assessment attempt ratio shows the strongest relationship with performance illustrate in figure 4, followed by click frequency and resource consistency, indicating key engagement predictors.

Real-time Pattern Detection:

Students completing assignments within 48 hours of posting demonstrated 23% higher final grades ($M = 72.1$, $SD = 12.3$) compared to those delaying beyond one week ($M = 58.7$, $SD = 15.4$), $t(32{,}591) = 287.3$, $p < .001$, $d = 0.961$. Assessment attempt ratios above 0.80 (i.e., attempting 80% or more of available assessments) were associated with a mean performance gain of 18.6 percentage points (95% CI [17.2, 20.0]). Conversely, students demonstrating sporadic engagement patterns (coefficient of variation > 0.65 in weekly log activity) exhibited 31% higher dropout rates and 27% lower completion grades.

4.5 Cross-Dataset Comparative Validation

In order to evaluate the robustness of the frameworks, the structural model was specified by estimating it individually on each of the four datasets on the empirically measured paths (PWB → AP, SE → AP, SRL → AP). Table 8 provides a comparison of path coefficients and model fit statistics. Competitive Intelligence Capability (CIC) is a conceptual and not an empirically measured moderator as indicated in Section 3.7. To this end, the cross-dataset validation does not involve the CIC × PWB interaction term, since there is no dataset that measures CIC on an institutional level. The convergence of the empirically estimated paths across datasets supports the evidence of the generalizability of the framework, and the conceptual moderation effect is a hypothetical suggestion that could only be empirically justified in the future.

Table 8: Cross-Dataset Structural Model Validation (Empirically Estimated Paths)

Path	PISA+CEPS (n≈20,000)	OULAD (n=32,593)	UCI (n=649)	Mean Effect	Variance
PWB → AP	0.267	0.251	0.289	0.269	$\sigma^2 = 0.0012$
SE → AP	0.341	0.328	0.356	0.342	$\sigma^2 = 0.0010$
SRL → AP	0.389	0.402	0.371	0.387	$\sigma^2 = 0.0008$
Model R^2	0.592	0.571	0.563	0.575	$\sigma^2 = 0.0008$
RMSEA	0.041	0.038	0.052	0.044	—

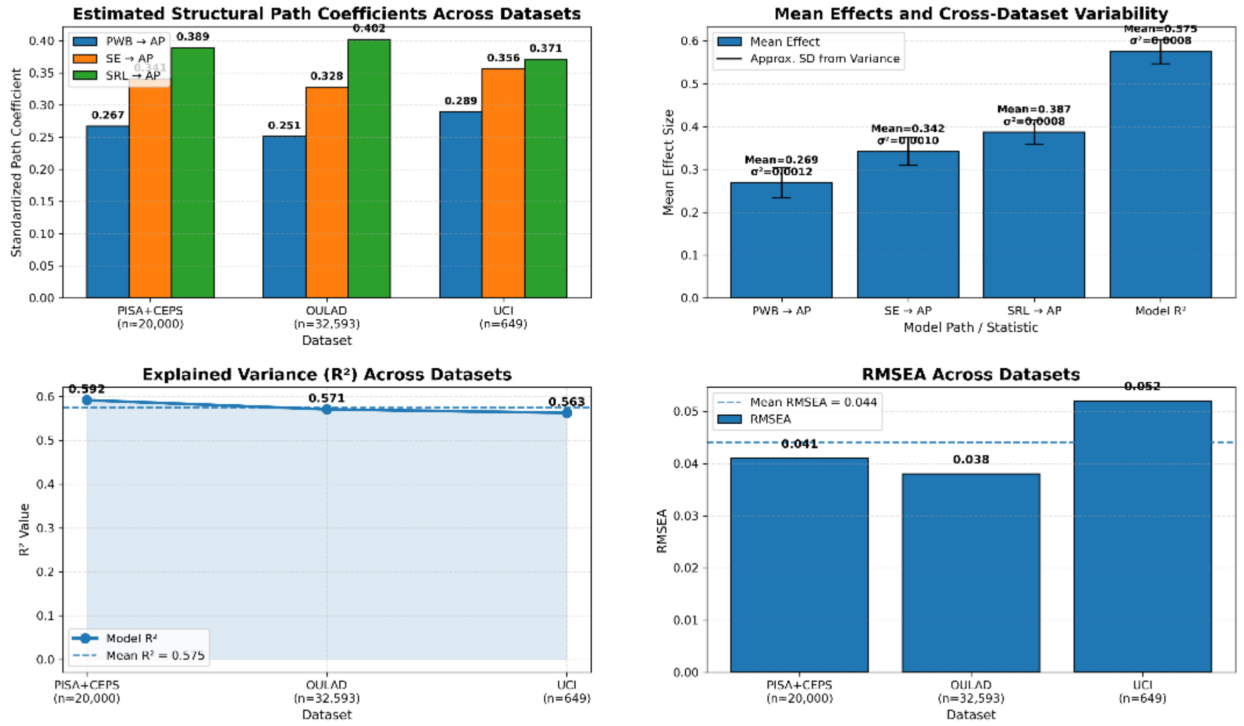

Figure 5: Cross-dataset validation of structural paths, mean effects, and model fit indices (R^2, RMSEA). SRL → AP is the strongest and most stable predictor across datasets, with low variance and consistent model fit ($R^2 \approx 0.57$, RMSEA < 0.05) as shown in figure 5.

Despite the consistency of findings across datasets, caution is required when interpreting generalizability due to structural heterogeneity and construct harmonization processes. The observed robustness reflects convergence of theoretical relationships rather than strict empirical equivalence across populations.

4.6 Well-Being Paradox: Performance–Psychological Well-Being Trade-Off

Analysis of PISA 2022 data ($n \approx 690{,}000$) revealed a critical nonlinear pattern between academic performance and psychological well-being. Table 9 quantifies performance and well-being metrics across quartiles of academic achievement.

Table 9: Academic Performance Quartiles and Well-Being Outcomes

Performance Quartile	Mean Math Score	Mean Well-being Index	% "Thriving" Status	Mean Life Satisfaction	Anxiety Index
Q1 (Lowest)	381 (43.2)	0.423	18.6%	6.8 (2.1)	0.687
Q2	467 (29.8)	0.518	34.2%	7.2 (1.9)	0.612
Q3	548 (24.1)	0.624	52.1%	7.6 (1.7)	0.523
Q4 (Highest)	637 (28.9)	0.521	38.4%	7.3 (1.8)	0.641

4.7 Discussion

The results indicate high levels of competitiveness of the proposed Competitive Intelligence Decision Support Framework (CI-DSF), which implies that an integrated analytical system makes behavioral, social, and psychological variables significant predictors of academic performance. The structural model demonstrates that self-regulated learning accounts the most ($\beta = 0.389$, $p < .001$), then social engagement ($\beta = 0.341$, $p < .001$) and psychological well-being ($\beta = 0.267$, $p < .001$) together makes a significant percentage of variance ($R^2 = 0.587$).

Competitive intelligence capability (CIC) conceptually moderates the relationship between well-being and performance, implying that a greater institutional intelligence capacity has the potential to enhance the ability to translate well-being into academic performance. This builds on previous studies by relating student-level behavioral and psychological processes to institution-level strategic intelligence views.

One of the contributions of the study is the discovery of a well-being paradox in which high-performing students have a lower level of life satisfaction and anxiety than moderately high performers. This fact shows that academic achievement does not always reflect better psychological well-being, which puts the focus on balanced performance strategies in higher education.

Individually, the ability to maintain engagement patterns has been linked with better performance, with better grades being reported among students who engage in early submissions and higher engagement rates. CIC, in theory, is a way in which student data might be converted into actionable insights at the organizational level and, therefore, could potentially make decisions more effective.

The inter-dataset synthetic integration method, which combines PISA, CEPS, OULAD and UCI datasets, presents the indications of the stable patterns in different settings. The fact that intraclass correlation (ICC = 0.957) is high and heterogeneity (I^2 = 2.1%) is low supports relationships that are constant and thus the strength of the proposed framework.

Nevertheless, there are a number of limitations which should be recognized. This cannot be caused because the synthetic integration does not allow the merging of individual-level data. The heterogeneity in measurements and contexts between datasets might cause residual heterogeneity. Notably, Competitive Intelligence Capability (CIC) is conceptualized as a variable instead of a measured variable; hence, moderation is just theoretical. The conditional effects and amplification patterns reported should be viewed as illustrative estimates and not generalizations.

Future studies ought to be directed at the creation and empirical confirmation of institutional-level measures of CIC and the use of multilevel modeling methods to evaluate the effects of moderation in hierarchical data.

Altogether, the CI-DSF is a scalable and integrative model of integrating academic performance, well-being, and behavioral analytics to form a strategic intelligence system with a significant implication of data-driven decision-making in higher education.

5. FINAL CONSIDERATIONS

The paper has formulated and tested a Competitive Intelligence Decision Support Framework (CI-DSF) which combines academic performance, student well-being, and behavioral engagement under a single analytical framework. The results show that the interaction of self-regulated learning, social engagement, and psychological well-being have a positive effect on student success and that self-regulated learning is the most significant predictor. Notably, the research offers conceptual support that institutional competitive intelligence capability may conceptually increase the efficiency of these factors and allow to translate student-level insights into superior academic performance. The moderation analysis simulated (Section 4.3) thus displays the theoretical direction and magnitude of this effect, but still empirical confirmation using directly measured institutional CIC is a valuable future research direction. While the proposed framework offers a promising direction for integrating educational analytics with competitive intelligence, it remains conceptual in several aspects, particularly regarding institutional intelligence capability. Therefore, the findings should be interpreted as theory-building rather than definitive empirical validation. Future research should focus on operationalizing CI at the institutional level and testing the framework in real-world university environments.

REFERENCES

Adewusi, A. O., Okoli, U. I., Adaga, E., Olorunsogo, T., Asuzu, O. F., & Daraojimba, D. O. (2024). Business intelligence in the era of big data: A review of analytical tools and competitive advantage. Computer Science & IT Research Journal, 5(2), 415–431. https://doi.org/10.51594/csitrj.v5i2.791

Alkhwaldi, A. F. (2024). Understanding the acceptance of business intelligence from healthcare professionals' perspective: An empirical study of healthcare organizations. International Journal of Organizational Analysis, 32(9), 2135–2163. https://doi.org/10.1108/IJOA-10-2023-4063

Arizmendi, C. J., Bernacki, M. L., Raković, M., Plumley, R. D., Urban, C. J., Panter, A. T., Greene, J. A., & Gates, K. M. (2023). Predicting student outcomes using digital logs of learning behaviors. Behavior Research Methods, 55(6), 3026–3054. https://doi.org/10.3758/s13428-022-01939-9

Cavallo, A., Sanasi, S., Ghezzi, A., & Rangone, A. (2021). Competitive intelligence and strategy formulation: Connecting the dots. Competitiveness Review, 31(2), 250–275. https://doi.org/10.1108/CR-01-2020-0009

Chun, Z., Ning, Y., Chen, J., & Wijaya, T. T. (2025). Exploring the interplay among artificial intelligence literacy, creativity, self-efficacy, and academic achievement. Education and Information Technologies, 30(15), 21283–21316. https://doi.org/10.1007/s10639-025-13617-2

de Souza Zanirato Maia, J., Bueno, A. P., & Sato, J. R. (2023). Applications of artificial intelligence models in educational analytics and decision making: A systematic review. World, 4(2), 288–313. https://doi.org/10.3390/world4020019

Fahd, K., & Miah, S. J. (2023). Designing and evaluating a big data analytics approach for predicting students' success factors. Journal of Big Data, 10(1), 159. https://doi.org/10.1186/s40537-023-00835-z

Fahd, K., Miah, S. J., & Ahmed, K. (2025). Predicting student performance in a blended learning environment. Applied Computing and Informatics, 21(3–4), 220–231. https://doi.org/10.1108/ACI-06-2021-0150

Li, Y., & Ho, E. S. (2024). What does PISA tell us about the paradoxes of students' well-being and academic competencies? Child Indicators Research, 17(4), 1443–1469. https://doi.org/10.1007/s12187-024-10146-1

Peng, Q., Zhang, Y., Liang, S., & Xu, M. (2025). Emotional and psychological determinants of student well-being. Acta Psychologica, 259, 105437. https://doi.org/10.1016/j.actpsy.2025.105437

Pratt, L., Bisson, C., & Warin, T. (2023). Bringing advanced technology to strategic decision-making: The decision intelligence/data science (DI/DS) integration framework. Futures, 152, 103217. https://doi.org/10.1016/j.futures.2023.103217

Ragazou, K., Passas, I., Garefalakis, A., & Zopounidis, C. (2023). Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. Discover Analytics, 1(1), 2. https://doi.org/10.1007/s44257-022-00002-3

Rana, S., Singh, V., & Chaturvedi, N. (2024). Emotional intelligence and mental well-being in higher education. Mental Health and Social Inclusion, 28(6), 927–940. https://doi.org/10.1108/MHSI-07-2023-0078

Rico-Juan, J. R., Cachero, C., & Macia, H. (2024). Influence of personality and LMS usage on learning performance. Applied Intelligence, 54(8), 6175–6197. https://doi.org/10.1007/s10489-024-05483-1

Singh, S., Rajest, S. S., Hadoussa, S., Obaid, A. J., & Regin, R. (Eds.). (2023). Data-driven intelligent business sustainability. IGI Global.

Sun, Y., & Liu, L. (2023). Structural equation modeling of academic resilience and well-being. BMC Psychology, 11(1), 347. https://doi.org/10.1186/s40359-023-01366-1

Tao, X., Shannon-Honson, A., Delaney, P., Li, L., Dann, C., Li, Y., & Xie, H. (2022). Data analytics on online student engagement data for academic performance modeling. IEEE Access, 10, 103176–103186. https://doi.org/10.1109/ACCESS.2022.3208953

Tong, B. (2025). Subjective well-being and educational performance in PISA. Social Sciences & Humanities Open, 11, 101486. https://doi.org/10.1016/j.ssaho.2025.101486

Wong, Z. Y., Liem, G. A., Chan, M., & Datu, J. A. (2024). Student engagement and its association with academic achievement and well-being. Journal of Educational Psychology, 116(1), 48.

Younas, M., El-Dakhs, D. A., & Jiang, Y. (2025). Emotional learning and its impact on student behavior and well-being. Scientific Reports, 15(1), 43856. https://doi.org/10.1038/s41598-025-28433-4

Yu, C. H., Xiao, Z., & Hanson, J. (2024). Machine learning for analyzing the relationship between well-being and academic performance. In Machine learning in educational sciences (pp. 267–292). Springer. https://doi.org/10.1007/978-981-99-9379-6_13