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ARTICLE

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OPERATIONALIZING COMPETITIVE INTELLIGENCE CAPABILITY IN HIGHER EDUCATION: A STRUCTURAL MODEL OF INSTITUTIONAL SENSING, SKILL SCAFFOLDING, AND ACADEMIC PERFORMANCE

OPERACIONALIZAÇÃO DA CAPACIDADE DE COMPETITIVE INTELLIGENCE NO ENSINO SUPERIOR: UM MODELO ESTRUTURAL DE SENSORIAMENTO INSTITUCIONAL, ESTRUTURAÇÃO DE COMPETÊNCIAS E DESEMPENHO ACADÊMICO

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ABSTRACT

Purpose: This study examines how Competitive Intelligence Capability (CICAP) can be operationalized in higher education as an organizational capability that transforms internal academic signals into strategic intelligence for institutional decision-making. It investigates the direct and indirect effects of CICAP on academic performance through skill-scaffolding mechanisms.

Methodology/Approach: A quantitative observational design was conducted using survey data from 399 students enrolled at 20 public and private universities in Bangladesh. Data were analyzed through descriptive statistics, reliability analysis, multiple linear regression, ANOVA, mediation analysis, and machine-learning algorithms (Random Forest and Gradient Boosting), within an organizational framework grounded in the Competitive Intelligence cycle.

Originality/Relevance: The study reconceptualizes lecturer-support indicators as internal organizational intelligence signals, integrating the Competitive Intelligence cycle, intelligence governance mechanisms, and dynamic capabilities into the higher education context, thereby bridging educational analytics and Competitive Intelligence literature.

Key Findings: Lecturer support showed a significant positive relationship with academic performance. Competitive Intelligence Capability demonstrated both direct and indirect effects on academic performance, with skill scaffolding partially mediating this relationship, highlighting the role of organizational intelligence in supporting evidence-based strategic decisions within universities.

Theoretical/Methodological Contributions: The study proposes an organizational framework for operationalizing Competitive Intelligence in higher education by integrating institutional sensing, intelligence governance, dynamic capabilities, and evidence-based decision-making. It also offers a reproducible analytical model that can support future empirical research on Competitive Intelligence Capability in educational institutions.

Keywords: Competitive Intelligence. Higher Education. Intelligence Governance. Academic Performance. Institutional Sensing. Evidence-Based Decision Making.

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RESUMO

Objetivo: Analisar como a Capacidade de Competitive Intelligence (Competitive Intelligence Capability – CICAP) pode ser operacionalizada no contexto do ensino superior como uma capacidade organizacional capaz de transformar sinais provenientes do ambiente acadêmico em inteligência estratégica para apoiar decisões institucionais. O estudo investiga os efeitos diretos e indiretos da CICAP sobre o desempenho acadêmico, mediado por mecanismos de desenvolvimento de competências (skill scaffolding).

Metodologia/abordagem: Foi realizada uma pesquisa quantitativa observacional com dados de 399 estudantes provenientes de 20 universidades públicas e privadas de Bangladesh. Os dados foram analisados por meio de estatística descritiva, análise de confiabilidade, regressão linear múltipla, ANOVA, análise de mediação e algoritmos de aprendizado de máquina (Random Forest e Gradient Boosting), operacionalizando um framework organizacional baseado no ciclo da Competitive Intelligence.

Originalidade/Relevância: O estudo reposiciona indicadores de apoio docente como sinais internos de inteligência organizacional, integrando o ciclo da Competitive Intelligence, mecanismos de governança da inteligência e capacidades dinâmicas ao contexto do ensino superior, aproximando a literatura educacional dos fundamentos da inteligência competitiva.

Principais Resultados: Os resultados evidenciam associação positiva entre apoio docente e desempenho acadêmico. A CICAP apresentou efeito significativo sobre o desempenho, tanto de forma direta quanto indireta, sendo parcialmente mediada pelos mecanismos de desenvolvimento de competências, demonstrando o potencial da inteligência organizacional para subsidiar decisões estratégicas em instituições de ensino superior.

Contribuições Teóricas/Metodológicas: O estudo propõe um framework organizacional para operacionalizar a Competitive Intelligence no ensino superior, integrando sensoriamento institucional, governança da inteligência, capacidades dinâmicas e suporte à decisão baseada em evidências, oferecendo um modelo analítico passível de reprodução em pesquisas futuras.

Palavras-chave: Inteligência Competitiva. Ensino Superior. Governança da Inteligência. Desempenho Acadêmico. Sensoriamento Institucional. Tomada de Decisão Baseada em Evidências.

1. INTRODUCTION

Universities increasingly operate in competitive environments where reputation, graduate outcomes, student retention, program quality, and responsiveness to stakeholder expectations function as strategic assets (Arnout et al., 2024). In such conditions, internal academic data are no longer merely administrative records; they become organizational signals that can inform institutional sensing, strategic decision-making, and sustainable competitive advantage (Dzenopoljac et al., 2024; Kero & Bogale, 2023; Wu et al., 2023). Competitive Intelligence (CI) provides the theoretical lens for understanding how such signals are collected, interpreted, disseminated, and converted into actionable decisions (Ranjan & Foropon, 2021).

Classical CI is concerned with the systematic transformation of fragmented information into decision-relevant intelligence through a structured cycle of planning, collection, processing, analysis, dissemination, and feedback (Wu et al., 2023). Within higher education, this logic can be extended inward: lecturer-support indicators, engagement patterns, online tutoring quality, feedback practices, and academic-performance perceptions can function as internal intelligence sensors (Ouyang et al., 2023; Susnjak et al., 2022). These sensors do not constitute CI by themselves; they become competitively meaningful only when embedded in governance routines that allow academic leaders to identify weak signals, prioritize interventions, and reconfigure teaching-support systems (Krakowski et al., 2022).

The present study therefore does not treat lecturer support as a purely pedagogical construct. Instead, lecturer-support data are interpreted as part of an institutional intelligence infrastructure. The core research problem is whether Perceived Institutional Competitive Intelligence Capability (CICAP) can be empirically operationalized and whether this capability contributes to academic performance through measurable instructional pathways. This framing responds directly to the need for studies that move beyond descriptive learning analytics and demonstrate how academic data can be organized into an institutional CI architecture (Wang & Yu, 2025).

Music-education and skill-acquisition literature is used only as a supporting theoretical vocabulary for classifying instructional support into cognitive-affective and skill-scaffolding pathways (Meng & Goopy, 2024). It is not the central disciplinary identity of the paper. The central identity of the study remains Competitive Intelligence: specifically, how universities can convert internal instructional signals into organizational knowledge for strategic action. Research on music classrooms has identified parallel cognitive-affective and skill-development trajectories that help explain how instructional support influences performance outcomes (Zhao et al., 2026; Zhang, 2025).

This paper analyzes survey data from 399 university students across twenty Bangladeshi universities. The empirical contribution is threefold. First, it operationalizes CICAP as an exploratory institutional intelligence construct. Second, it tests structural pathways linking CICAP, lecturer support, skill scaffolding, and academic performance. Third, it clarifies the boundary between learning analytics as a data source and Competitive Intelligence as an organizational capability that requires governance, interpretation, and decision feedback. The Bangladeshi context is particularly relevant because prior studies have documented substantial variation in teacher–student interaction quality and online tutoring support across higher education institutions (Mallik, 2023a; Mallik, 2023b; Sarker et al., 2025; de las Heras-Rosas & Herrera, 2021).

This paper addresses that gap by analysing a dataset of 399 university students drawn from twenty Bangladeshi universities (Yağcı, 2022). The contribution is fourfold. First, it reframes lecturer-support indicators as internal organizational intelligence signals rather than as isolated educational variables (Ouyang et al., 2023; Susnjak et al., 2022). Second, it operationalizes CICAP as an exploratory institutional CI capability composite and tests its direct and indirect association with academic performance (Dzenopoljac et al., 2024; Kero & Bogale, 2023; Wu et al., 2023). Third, it distinguishes between relational lecturer support and skill scaffolding to identify the pathway through which CI-related capability becomes performance-relevant (Liu, 2021; Zhao et al., 2026). Fourth, it offers a reproducible analytical pipeline that can support institutional sensing, benchmarking, and evidence-based decision-making while acknowledging that full organizational validation requires future manager-level and institutional-level evidence (Abuzinadah et al., 2023; Sánchez-Sánchez et al., 2024; Krakowski et al., 2022).

The rest of the paper is structured as follows. The second section introduces the theoretical basis and the relevant literature review, where a comparative analysis of previous studies is presented in tabular form. The third section explains the methodology employed, the data used, the processing approach, and the equations for analysis. The fourth section details the results in terms of description, correlation, regression analysis, and machine learning, while providing an explanation of the trajectories (Adefemi & Mutanga, 2025).

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Lecturer Support and Academic Performance

The concept of lecturer support in the modern literature is seen as a multidimensional concept that includes emotional, instructional, and informational aspects (Prananto et al., 2025). Perceived social support and academic pressure are identified as two mechanisms that mediate the relationship between a strong teacher-student relationship and academic engagement, with the mediation effects being more significant in Chinese university samples (Liu, 2024). This systematic review by Prananto et al. (2025) supports the consistent findings that perceived teacher support is linked to higher levels of student engagement in higher education settings from 2014 to 2024. However, some of the indicators are not symmetrical, and some authors find that the variance in academic achievement is greater across dimensions that reflect instruction and feedback than across affective dimensions (Zhou et al., 2022).

Carmona-Halty et al. (2024) employed a four-wave panel design to demonstrate the mediation effects between teacher-student relationships and academic outcomes by study-related positive emotions and academic psychological capital among high school students. The study by Wang, Zhang and Wang (2024) reveals that academic self-efficacy and intrinsic motivation chain-mediates the relationship between self-efficacy beliefs and academic burnout, which in turn affects performance. Shen and colleagues (2024) have shown that teacher emotional support leads to academic involvement via positive academic emotions and mastery-approach goals among Chinese college students. Both of these studies conclude that lecturer support effects on performance are indirect and that intermediate psychological resources account for the vast majority of the predictive power (Liu et al., 2023).

2.2 Cognitive and Skill-Acquisition Trajectories in School-Based Music Education

Studies of school-based music education in Chinese classrooms have produced a useful trajectory vocabulary for analysing how lecturer support shapes learning (Sun, 2023). Zhao and colleagues report that classroom climate dimensions, including teacher-student interaction and physical environment, influence music aesthetic literacy through the mediating role of self-efficacy (Zhao et al., 2026). Zhang shows that engagement and metacognitive factors predict performance outcomes among advanced Chinese music students, with cognitive confidence operating as a positive mediator (Zhang, 2025). Song demonstrates that AI-powered learning tools shape cognitive load, well-being, and academic success in Chinese music students, with technology acceptance acting as a key moderator (Song, 2025). Wang and colleagues provide quasi-experimental evidence that game-based piano learning reshapes music knowledge acquisition among Chinese elementary pupils (Y. Wang et al., 2026).

The skill-acquisition perspective in music education traces five canonical phases of expertise, beginning with explicit instruction, moving through practice and proceduralisation, and ending with autonomous high-level performance (Sala & Gobet, 2020). Initial teacher-education studies of Chinese music teachers stress the importance of pedagogical content knowledge, which scaffolds learners along this trajectory (Meng & Goopy, 2024). The trajectory framework is therefore well suited to lecturer-support analytics because lecturer behaviours can be naturally classified as either cognitive-affective scaffolds, which create the climate for learning, or skill-acquisition scaffolds, which structure the practice of disciplinary skills (Johansen & Jeno, 2023).

2.3 Competitive Intelligence as Strategic Organizational Capability in Universities

Competitive intelligence is the organizational competence to convert internal and external information into a decision-making knowledge in a systematic way by following a structured intelligence cycle of planning, collection, processing, analysis, dissemination and feedback (Ranjan & Foropon, 2021; Wu et al., 2023). In this tradition, competitive intelligence is not just a single tool or dashboard, but a multi-layered architecture in which a variety of sensors, analytic routines, governance arrangements and decision channels are thoughtfully linked in a way that will create sustainable competitive edge. According to the resource-based perspective, this type of architectures is hard for competitors to duplicate because of the value, rarity, inimitable, and non-substitutable nature of information assets and analytic routines (Kero & Bogale, 2023). The knowledge-based view generalizes this view, suggesting that the success lies not in the integration of content knowledge but in the integration of specialized knowledge in a university setting, which in this case refers to the integration of teaching, learning and analytic expertise (Dzenopoljac et al., 2024).

Competitive intelligence is applied at least four layers inside the university, summarized later in Figure 5. The sensor layer gathers signals that are relevant for the classroom level, including lecturer-support indicators, attendance, traces of the learning-management-system, and student feedback. The analytic layer performs the intelligence cycle on these signals, using descriptive, diagnostic, predictive and prescriptive analytics. The governance layer is responsible for converting analytic results into authority to make decisions by establishing committees, conducting ethical reviews, managing data stewardship, and assigning follow-up accountability. The decision level deals with instructional design, professional development, resource allocation, and curricular reform. Dynamic capabilities theory serves as the glue between these layers, defining the faculty's ability to hear weak signals, to discover the analytical opportunities those signals present, and to reconfigure its teaching processes as the deeper capability that will enable it to gain advantage amid the turbulence of demographic, technological and policy conditions (Krakowski et al., 2022).

It is significant that there is a difference between business intelligence, competitive intelligence and decision intelligence, for the present argument. Business intelligence is mainly about reporting and dashboards of internal data, as said by Adewusi et al., 2024. Competitive intelligence is the larger process of strategic intelligence gathering, sharing and also incorporating an explicit connection with sustainable competitive advantage (Ranjan & Foropon, 2021; Wu et al., 2023). Decision intelligence also extends the cycle by viewing the output of each analytical process as an input to a process of structured decision; and by monitoring the impact that the decision-making process has on the outcomes. The structure used in this paper is taken from all three traditions: the competitive intelligence cycle, business intelligence data-pipelines, and decision intelligence choice and feedback.

This architecture has been described in a small but growing number of works specific to the university. In public universities, competitive intelligence is considered as a strategic tool for student recruitment, and in this instance, it is used to defend the positioning of the institution when performing market scanning from the outside (Mgweba et al., 2024). In the current era of growing competition for students and resources, business-intelligence pipelines have become a key element of the competitive advantage of higher-education institutions, according to Adewusi and colleagues (2024). Data-driven decision making, as exemplified by the model of Baker, does transform governance as is evident in the Chinese higher-education institution (HEI) context as it is represented by Kalim and Bibi (2023). The present study is theoretically extended by linking the intelligence cycle to a particular set of sensors at the classroom level, namely the 12 lecturer-support indicators; and empirically extended by incorporating a five-item Perceived Institutional CI Capability composite (CICAP) and testing the structural relationship between CICAP, lecturer support, skill scaffolding, and academic performance using bootstrap mediation analysis (Section 4.7).

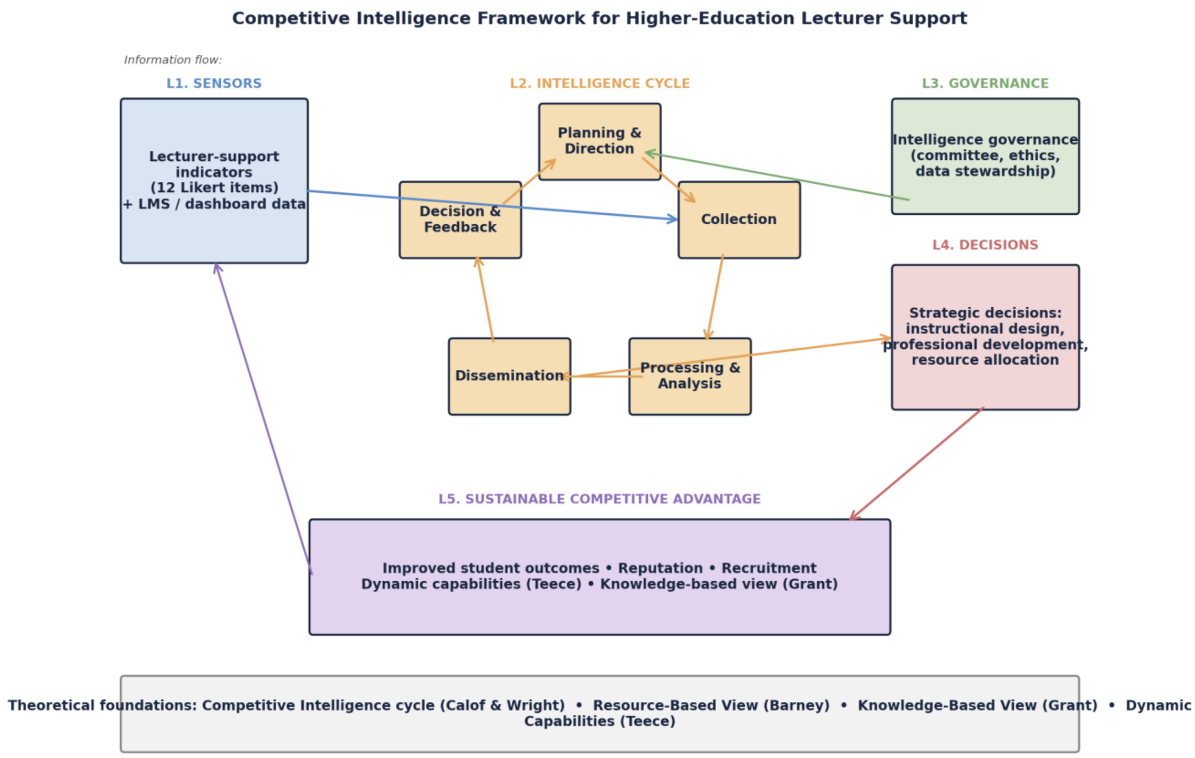

Figure 1. Organizational competitive-intelligence framework for lecturer-support analytics in higher education

Figure 1 visualizes the five-layer architecture that organizes the framework. The sensor layer (L1) collects classroom-level signals; the intelligence cycle (L2) transforms those signals through planning, collection, processing and analysis, dissemination, and decision feedback; the governance layer (L3) supplies institutional accountability and ethical oversight; the decision layer (L4) selects instructional, developmental, and resource interventions; and the strategic outcome layer (L5) accumulates sustainable competitive advantage through improved student outcomes, enhanced reputation, and stronger recruitment performance. The shaded ribbon at the foot of the figure names the four foundational theoretical traditions on which the architecture rests: the competitive-intelligence cycle, the resource-based view, the knowledge-based view, and the dynamic-capabilities perspective. Section 4.7 reports the empirical structural-model evidence for the analytic and decision layers of this architecture.

2.4 Competitive Intelligence in Higher Education

In the present study, learning analytics is not treated as equivalent to Competitive Intelligence. Learning analytics supplies data; Competitive Intelligence supplies the organizational process through which data are transformed into actionable institutional knowledge (Ranjan & Foropon, 2021; Wu et al., 2023). This distinction is essential for JSCI alignment. A dashboard, prediction model, or benchmarking table becomes CI only when it is connected to the intelligence cycle, governance responsibility, decision authority, and feedback mechanisms that influence institutional strategy (Krakowski et al., 2022; Dzenopoljac et al., 2024). Therefore, lecturer-support analytics are positioned here as internal sensing inputs, while CICAP represents the university's perceived capability to convert those inputs into strategic academic action (Ouyang et al., 2023; Adewusi et al., 2024).

Inside the institution, the equivalent of market intelligence is learning analytics, which transforms classroom and platform data into actionable insights (Bennett & Folley, 2020). Recent reviews of learning-analytics dashboards in higher education argue that the discipline is becoming increasingly oriented towards learning rather than reporting, with dashboards designed to guide both teachers and students (Susnjak et al., 2022). Susnjak, Ramaswami, and Mathrani show that explainable analytics and counterfactual reasoning are now central to providing actionable insights to learners (Paulsen & Lindsay, 2024). The intersection of competitive intelligence and learning analytics provides the conceptual base for the present study, in which lecturer-support indicators are treated as inputs to a benchmarking pipeline that can be operationalised institutionally (Kalim & Bibi, 2023).

2.4.1 Institutional Operationalization of Competitive Intelligence Capability

For this study, Competitive Intelligence Capability is operationalized as a multi-layered institutional capability rather than as a single analytical output. The first layer is the sensing layer, represented by classroom-level and instructional signals. The second layer is the analytical layer, where these signals are processed through descriptive, correlational, regression, and benchmarking procedures. The third layer is the governance layer, which gives organizational meaning to the analysis by assigning responsibility for interpretation, ethical oversight, and follow-up decisions. The fourth layer is the decision-feedback layer, where intelligence outputs inform professional development, instructional redesign, resource allocation, and academic-support priorities.

CICAP is therefore interpreted as an exploratory proxy for students' perception of institutional information-provision capability. Its indicators capture whether the university environment communicates goals clearly, responds to academic needs, provides supportive digital and classroom infrastructure, and transmits positive expectations. These indicators do not fully exhaust the concept of CI; however, they provide a measurable starting point for examining how institutional sensing capability becomes connected to academic outcomes. This distinction prevents the study from reducing CI to dashboards or educational data mining alone.

2.5 Predictive Modelling of Student Performance

Educational data mining has produced a large body of evidence that machine-learning models can predict student performance with useful accuracy (Rastrollo-Guerrero et al., 2020). Angeioplastis and colleagues show that machine-learning algorithms applied to Moodle data effectively detect high-performing courses and at-risk students in higher-education contexts (Angeioplastis et al., 2025). Wang and Yu propose a Taylor-expansion-augmented logistic regression for performance prediction in online learning environments and report substantial gains over baseline methods (Wang & Yu, 2025). Abuzinadah and colleagues integrate convolutional features with classical machine learning to predict performance from Moodle records, while Chen and colleagues use genetic algorithms to optimise random-forest components for academic-outcome prediction (Abuzinadah et al., 2023; Chen et al., 2024).

In ensemble-based studies, gradient boosting and XGBoost frequently outperform individual learners, particularly when class imbalance is addressed through resampling (Yağcı, 2022). Hassan and colleagues report that Random Forest with SMOTE balancing predicts students' engagement and final outcomes in virtual learning environments with strong precision-recall performance (Jawad et al., 2022). A recent study using data from Complutense University of Madrid applies Random Forest and XGBoost to identify the determinants of academic performance from 8,700 first-year records (Sánchez-Sánchez et al., 2024). These methodological precedents motivate the use of ordinary-least-squares regression alongside Random Forest and Gradient Boosting in the present study (Le Quy et al., 2022).

2.6 Comparison Table of Related Studies

Table 1 summarises a representative subset of recent studies that connect lecturer-support practices, academic performance, learning analytics, and competitive intelligence. It indicates how the present study differs from prior work by combining a trajectory-based theoretical layer with a competitive-intelligence interpretive frame and an explicit machine-learning benchmark.

Table 1. Comparison of selected related studies and positioning of the present work

Ref.	Author / Year	Context / Sample	Method / Approach	Key Finding / Gap Filled
(Prananto et al., 2025)	Prananto et al. (2025)	Higher-ed students, 13 studies, 2014–2024	PRISMA systematic review of teacher support and engagement	Confirms multidimensionality of perceived teacher support; lacks predictive modelling
(Liu, 2024)	Liu (2024)	1,058 Chinese university students	SEM with mediation	Teacher-student relationship → engagement via social support and reduced pressure
(Carmona-Halty et al., 2024)	Carmona-Halty et al. (2024)	Chilean high-school students, 4 waves	Longitudinal mediation	Positive emotions and academic PsyCap mediate TSR-performance link
(Shen et al., 2024)	Shen et al. (2024)	464 Chinese college students	Mediation/moderation regression	Teacher emotional support → engagement via positive emotions and mastery goals
(Zhao et al., 2026)	Zhao et al. (2026)	Chinese non-music majors	PLS-SEM mediation	Classroom climate → music aesthetic literacy through self-efficacy
(Zhang, 2025)	Zhang (2025)	Advanced Chinese music students	Mediation modelling	Engagement and metacognition predict performance trajectories
(Song, 2025)	Song (2025)	454 Chinese music students	TAM, regression	AI tools shape cognitive load, well-being, and academic success
(Y. Wang et al., 2026)	Wang et al. (2026)	Chinese elementary pupils, piano	Quasi-experimental pretest-posttest	Gamified instruction strengthens skill-acquisition trajectory
(Mgweba et al., 2024)	Mgweba et al. (2024)	South-African public universities	Qualitative case study	Competitive intelligence as student-recruitment lever; classroom dimension absent
(Susnjak et al., 2022)	Susnjak et al. (2022)	Higher-ed dashboards	Systematic synthesis with XAI	Learning analytics dashboards shifting from descriptive to predictive insights
(Angeioplastis et al., 2025)	Angeioplastis et al. (2025)	450 students, Moodle, 9 semesters	Five-algorithm ML benchmark	Correlated courses improve binary prediction; teacher-support indicators not tested
(Wang & Yu, 2025)	Wang & Yu (2025)	Online learning records	Taylor-augmented logistic regression	Improved baseline accuracy in online performance prediction
(Chen et al., 2024)	Chen et al. (2024)	Educational data, multi-source	Genetic-algorithm-optimised RF	Optimised RF outperforms vanilla models in performance prediction
(Sánchez-Sánchez et al., 2024)	Sanz-Angulo et al. (2024)	8,700 first-year Spanish students	RF + XGBoost feature selection	Identifies key academic determinants but ignores instructional support
—	This study (2026)	399 students, 20 Bangladeshi universities	OLS + RF + GBM + trajectory analysis under CI framework	Operationalises lecturer-support CI; decomposes cognitive vs skill trajectories

3. METHODOLOGY

3.1 Study Design

The study adopts a quantitative observational design combined with an analytical pipeline organised under a competitive-intelligence frame (Ranjan & Foropon, 2021). Observational designs preserve the ecological validity of real-world classroom interactions and avoid the laboratory artefacts of controlled experiments (Angeioplastis et al., 2025). The framework treats lecturer-support indicators as institutional sensors that feed an evidence-based benchmarking process, parallel to the way market signals feed a corporate competitive-intelligence routine (Adewusi et al., 2024). The pipeline is structured into seven sequential stages, visualised in Figure 1 (see Section 3.6), and is reproducible in a Kaggle-compatible Python environment with optional GPU acceleration through cuML and cuDF (Sánchez-Sánchez et al., 2024). The empirical scope of the study is intentionally limited to student-perceived institutional and instructional signals. The dataset does not include interviews with university managers, administrative case-study records, committee minutes, or longitudinal institutional-performance indicators. Therefore, the study should be interpreted as an exploratory quantitative operationalization of CI capability rather than as a complete organizational validation of a university CI system. This boundary is important because the analysis demonstrates the sensing and analytical layers of CI, while the governance and managerial-decision layers are specified theoretically and identified as priorities for future institutional validation.

3.2 Dataset Description

The data collected for the study comprises 399 valid answers that were obtained using an online survey distributed among undergraduate students studying in 20 public and private universities of Bangladesh, such as DIU, HSTU, BUET, JU, BU, DU, CoU, KUET, IU, KU, KYAU, BDU, NpMC, RUET, AIUB, JnU, SUST, BRAC, COU, and BAU (Mallik, 2023a). The tool includes information on 29 variables, which include demographic information, 12 questions concerning lecturer support, 3 related to academic performance, and 2 open-ended comments, and aggregated scoring fields (Prananto et al., 2025). The twelve lecturer-support items are measured on a five-point Likert scale and cover interaction (INTRCT), academic goals (AGOALS), assistance (ASSIS), positive attitude (POSTV), classroom climate (CCT), supportiveness (SUPPO), relationship quality (RLTN), encouragement (ENCG), feedback (FDBC), improvement orientation (IMPR), teaching effectiveness (TEFF), and online tutoring (ONLN) (Prananto et al., 2025). Academic-performance items capture academic balance (ACBL), self-rated academic performance (APER), and online-learning impact (ONLIMP) (Prananto et al., 2025).

Variables are listed and defined in Table 2 alongside their measurement scale and analytical role. Each respondent was assigned an aggregate Total Score and a four-tier engagement label, with categories Extremely High TSR (n = 105), High TSR (n = 168), Medium TSR (n = 75), and Poorly Engaged TSR (n = 51), where TSR denotes teacher-student relationship strength (Mallik, 2023b).

Table 2. Variable definitions and analytical roles in the lecturer-support dataset

Variable	Type	Scale	Description
AGE	Demographic	Coded 2–3	Age band of respondent
GDR	Demographic	Coded 1–3	Self-reported gender category
UL	Demographic	Coded 1–3	University-year level
INTRCT	Predictor	1–5 Likert	Quality of lecturer-student interaction
AGOALS	Predictor	1–5 Likert	Clarity and communication of academic goals
ASSIS	Predictor	1–5 Likert	Availability of academic assistance
POSTV	Predictor	1–5 Likert	Positive attitude expressed by lecturer
CCT	Predictor	1–5 Likert	Quality of classroom climate
SUPPO	Predictor	1–5 Likert	Overall supportiveness in academic matters
RLTN	Predictor	1–5 Likert	Strength of teacher-student relationship
ENCG	Predictor	1–5 Likert	Encouragement to participate and excel
FDBC	Predictor	1–5 Likert	Quality and timeliness of feedback
IMPR	Predictor	1–5 Likert	Improvement-oriented coaching
TEFF	Predictor	1–5 Likert	Teaching effectiveness rating
ONLN	Predictor	1–5 Likert	Quality of online tutoring and support
ACBL	Outcome	1–5 Likert	Perceived academic balance
APER	Outcome	1–5 Likert	Self-rated academic performance
ONLIMP	Outcome	1–5 Likert	Online-learning impact on outcomes
LSI	Derived	1–5 mean	Lecturer Support Index, mean of twelve predictors
COG_SUP	Derived	1–5 mean	Cognitive-affective trajectory composite
SKI_SUP	Derived	1–5 mean	Skill-acquisition trajectory composite
CICAP	Derived	1–5 mean	Perceived Institutional Competitive Intelligence Capability composite based on AGOALS, ASSIS, CCT, ONLN, and POSTV
REL_SUP	Derived	1–5 mean	Relational lecturer-support composite based on INTRCT, SUPPO, RLTN, and ENCG
SKILL	Derived	1–5 mean	Skill-scaffolding composite based on FDBC, IMPR, and TEFF
API	Outcome	1–5 mean	Academic Performance Index, mean of three outcome items
Total Sum	Summary	27–65	Aggregate of all twelve lecturer-support indicators

3.3 Data Preprocessing

Preprocessing was carried out within a Python notebook designed for Kaggle, using pandas 2.x for tabular operations, numpy for matrix manipulations, and scikit-learn for standardisation and model fit (Sánchez-Sánchez et al., 2024). In instances where GPU support was available, the exact same preprocessing pipeline was applied with cuDF and cuML to yield identical results in a shorter time (Sánchez-Sánchez et al., 2024). The data was first read in from the CSV with strict type specification for Likert predictors, followed by schema validation for any inconsistent code types (Angeioplastis et al., 2025). The open-ended responses, the email field, the date-time stamp, and the statistics columns were discarded since they do not contain any analytically relevant data (Prananto et al., 2025).

Missingness analysis revealed that all Likert questions had no missing values, whereas only the Score variable in the demographics section had missing value and thus, was excluded from the dataset (Jawad et al., 2022). Logical consistency was verified by confirming that Total Score matched the sum of twelve Likert questions with all records satisfying the addition constraint (Sánchez-Sánchez et al., 2024). Continuous predictors were standardised using z-score normalisation prior to machine-learning fitting, although the original Likert scale was preserved for the regression interpretation and for the descriptive analysis (Le Quy et al., 2022). Feature selection used Pearson correlation with the API, univariate F-tests, and Random Forest impurity-based importance, retaining all twelve indicators because each carries theoretical justification grounded in the support literature (Angeioplastis et al., 2025; Prananto et al., 2025).

3.4 Feature Construction and Trajectory Mapping

Following the cognitive and skill-acquisition trajectory framework derived from school-based music-education research (Sun, 2023), the twelve lecturer-support indicators were partitioned into two interpretive trajectories. The cognitive-affective trajectory (COG_SUP) groups INTRCT, AGOALS, POSTV, CCT, RLTN, and ENCG, capturing the relational and motivational climate that scaffolds higher-order cognition (Zhao et al., 2026). The skill-acquisition trajectory (SKI_SUP) groups ASSIS, SUPPO, FDBC, IMPR, TEFF, and ONLN, capturing the explicit instructional, feedback, and tutoring structures that scaffold disciplinary skill development (Sala & Gobet, 2020). The Lecturer Support Index (LSI) is the unweighted mean of all twelve indicators, and the Academic Performance Index (API) is the unweighted mean of ACBL, APER, and ONLIMP (Prananto et al., 2025).

3.5 Analytical Equations

Five equations operationalise the analytical pipeline. Equation (1) defines the Lecturer Support Index. Equation (2) defines the Academic Performance Index. Equation (3) gives the cognitive and skill-acquisition trajectory composites. Equation (4) specifies the multiple linear regression model for API as a function of the twelve indicators and demographic covariates, and Equation (5) defines the standardised z-score transformation used in preprocessing.

$$LSI_i = (1/12) \times \Sigma_{j=1}{}^{12} X_{ij} \qquad (1)$$

The Lecturer Support Index for respondent i is indicated by LSI_i, whereas X_{ij} represents the answer provided by the i-th respondent with regards to the j-th lecturer support indicator. It is worth mentioning that the unweighted average maintains the original interpretative scale, which was designed using a five-point scale (Prananto et al., 2025).

$$API_i = (1/3) \times (ACBL_i + APER_i + ONLIMP_i) \qquad (2)$$

In Equation (2), API_i is the Academic Performance Index of respondent i, calculated as the unweighted mean of three self-reported academic-performance items: academic balance ($ACBL_i$), self-rated academic performance ($APER_i$), and online-learning impact ($ONLIMP_i$). The construct mirrors latent-performance indices used in recent higher-education survey studies (Shen et al., 2024).

$$COG\_SUP_i = (1/6) \times \Sigma\_\{k \in C\}\, X_{ik}\,; \quad SKI\_SUP_i = (1/6) \times \Sigma\_\{k \in S\}\, X_{ik} \qquad (3)$$

In Equation (3), C is the cognitive-affective indicator subset, defined as {INTRCT, AGOALS, POSTV, CCT, RLTN, ENCG}, and S is the skill-acquisition indicator subset, defined as {ASSIS, SUPPO, FDBC, IMPR, TEFF, ONLN}. The trajectory decomposition follows the theoretical mapping established in school-based music-education research and provides the analytical bridge to the competitive-intelligence interpretation (Sala & Gobet, 2020; Sun, 2023).

$$API_i = \beta_0 + \Sigma_{j=1}{}^{12} \beta_j\, X_{ij} + \gamma_1\, AGE_i + \gamma_2\, GDR_i + \gamma_3\, UL_i + \varepsilon_i \qquad (4)$$

In Equation (4), β_0 is the regression intercept, β_j are the coefficients of the twelve lecturer-support indicators, γ_1, γ_2, γ_3 are the coefficients of the demographic covariates, and ε_i is the error term. The model is fitted by ordinary least squares on the centred predictors. Statistical inference uses the t statistic and the F statistic, with significance reported at the 0.05, 0.01, and 0.001 thresholds (Le Quy et al., 2022).

$$Z(X_{ij}) = (X_{ij} - \mu_j) \,/\, \sigma_j \qquad (5)$$

In Equation (5), $Z(X_{ij})$ is the z-score-standardised version of indicator j for respondent i, μ_j is the sample mean, and σ_j is the sample standard deviation. Standardisation makes the input space comparable for distancebased and tree-based learners and stabilises the optimisation of gradient-boosting models (Sánchez-Sánchez et al., 2024).

3.6 Analytical Pipeline and Algorithm Description

Figure 2 gives an overview of the seven-step analysis pipeline. The first step is to ingest the raw CSV data using strict d-type checking. The second step is to clean the dataset by removing non-Likert scale variables and checking logical coherence. The third step consists of encoding categorical data and then applying z-score normalization. In the fourth step, both sets of new variables for LSI, COG_SUP, and SKI_SUP are constructed, along with the target for API.

Stage 6a performs statistical inference using OLS regression and ANOVA, and Stage 6b performs predictive modelling using Linear Regression, Random Forest, and Gradient Boosting with five-fold cross-validation. Stage 7 produces the competitive-intelligence synthesis by benchmarking groups, profiling trajectories, and segmenting risk (Adewusi et al., 2024; Paulsen & Lindsay, 2024).

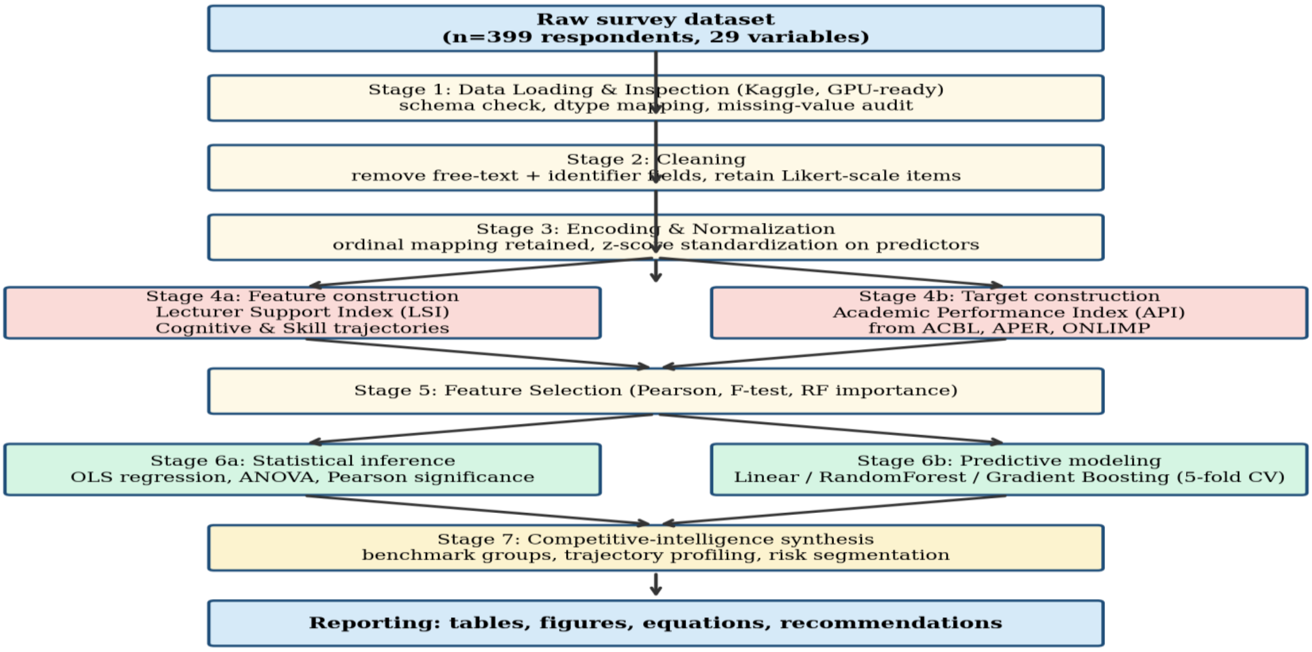

Figure 2. Stepwise analytical pipeline for the lecturer-support competitive-intelligence study

Algorithm 1 summarises the sequence of operations. Inputs are the raw CSV path, the indicator schema, and the trajectory mapping. Outputs are the descriptive table, the correlation matrix, the regression coefficients, the cross-validated machine-learning scores, the feature-importance ranking, and the four-tier benchmarking summary. The procedure begins by loading the file, dropping non-Likert columns, and verifying the schema. It then constructs LSI, COG_SUP, SKI_SUP, and API, standardises predictors, fits the regression by ordinary least squares, fits Random Forest and Gradient Boosting under five-fold cross-validation, computes Pearson correlations and one-way ANOVA across the four tiers, and finally produces the figures and tables (Angeioplastis et al., 2025; Le Quy et al., 2022).

3.7 Tools and Computing Environment

Analyses were executed in Python 3.11 inside a Kaggle notebook using pandas 2.x, NumPy, scikit-learn 1.5, scipy, and matplotlib (Sánchez-Sánchez et al., 2024). GPU acceleration is optional and requires the cuDF and cuML libraries, in which case the pipeline runs unchanged through a context switch between pandas-style and cudf-style frames (Sánchez-Sánchez et al., 2024). Random states were fixed to 42 for reproducibility, and all stochastic operations, including the train-test split and the cross-validation shuffling, used identical seeds (Angeioplastis et al., 2025). The full Python source is presented in the supplementary material under the data-availability statement.

3.8 Ethical Considerations

Data was obtained using an online survey conducted on a voluntary basis, where participants provided their informed consent by participating in the survey (Prananto et al., 2025). Fields that could identify the person, such as an e-mail address, were not included in the analytic dataset, and only anonymous Likert scale and demographic questions were analyzed (Mallik, 2023a). This research poses minimal ethical risk to the participants and is consistent with the Helsinki Declaration.

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

There are 399 valid cases in the data from twenty different Bangladeshi universities that have thirty-six different departments (Mallik, 2023a). Table 3 shows the summary statistics on the lecturer support scale, trajectory composite scales, and performance items. The values for Total Score range from 27 to 65 and its mean and standard deviation is 49.96 and 8.95, respectively (Mallik, 2023b). It indicates the presence of variability in terms of lecturer support across various cases. The four-level benchmarking is almost uniform; there are 168, 105, 75, and 51 cases of High TSR, Extremely High TSR, Medium TSR, and Poorly Engaged TSR, respectively.

Variable	Mean	Std. Dev	Min	Max	Median
INTRCT	3.45	1.15	1	5	4
AGOALS	3.35	1.19	1	5	3
ASSIS	3.39	1.12	1	5	4
POSTV	3.34	1.06	1	5	3
CCT	3.06	1.18	1	5	3
SUPPO	3.10	1.20	1	5	3
RLTN	3.31	1.18	1	5	3
ENCG	3.40	1.18	1	5	4
FDBC	3.13	1.16	1	5	3
IMPR	3.20	1.22	1	5	3
TEFF	3.31	1.16	1	5	3
ONLN	2.74	1.22	1	5	3
LSI	3.23	0.74	1.42	4.50	3.33
COG_SUP	3.32	0.85	1.50	5.00	3.33
SKI_SUP	3.15	0.81	1.33	4.83	3.17
ACBL	2.86	1.03	1	5	3
APER	2.59	0.99	1	5	2
ONLIMP	2.32	0.90	1	5	2
API	2.59	0.59	1.00	4.33	2.67
Total Sum	49.96	8.95	27	65	53

Table 3. Descriptive statistics of lecturer-support indicators and academic-performance items (n = 399)

In comparison to the rest of the twelve factors, the highest means were obtained in the case of INTRCT, ENCG, and ASSIS, which shows that these concepts are considered well-established compared to other factors (Prananto et al., 2025). On the contrary, ONLN was found to have the lowest mean value, which is 2.74, showing that online tutoring is not on par with face-to-face tutoring yet (Sarker et al., 2025). While the skill acquisition pathway factor SKI_SUP showed a mean value of 3.15, the cognitive-affective factor COG_SUP showed 3.32, demonstrating a structure disparity in this regard (Sala & Gobet, 2020).

4.2 Exploratory Data Analysis

The outcomes of exploratory data analysis are illustrated in Figure 3 below, which includes the total score distribution by each level, the distribution of the API for each level, the LSI-AP correlation graph, and the trajectory graph comparison. There is a distinction made between the Poorly Engaged TSR and Extremely High TSR, while both Medium and High levels share a common part of the score distribution (Prananto et al., 2025). The boxplot graph confirms the upward trend of the API score from Poorly Engaged TSR to Extremely High TSR, while the scatter graph indicates a relatively weak positive relationship between the LSI and API scores, r = 0.329 (Shen et al., 2024).

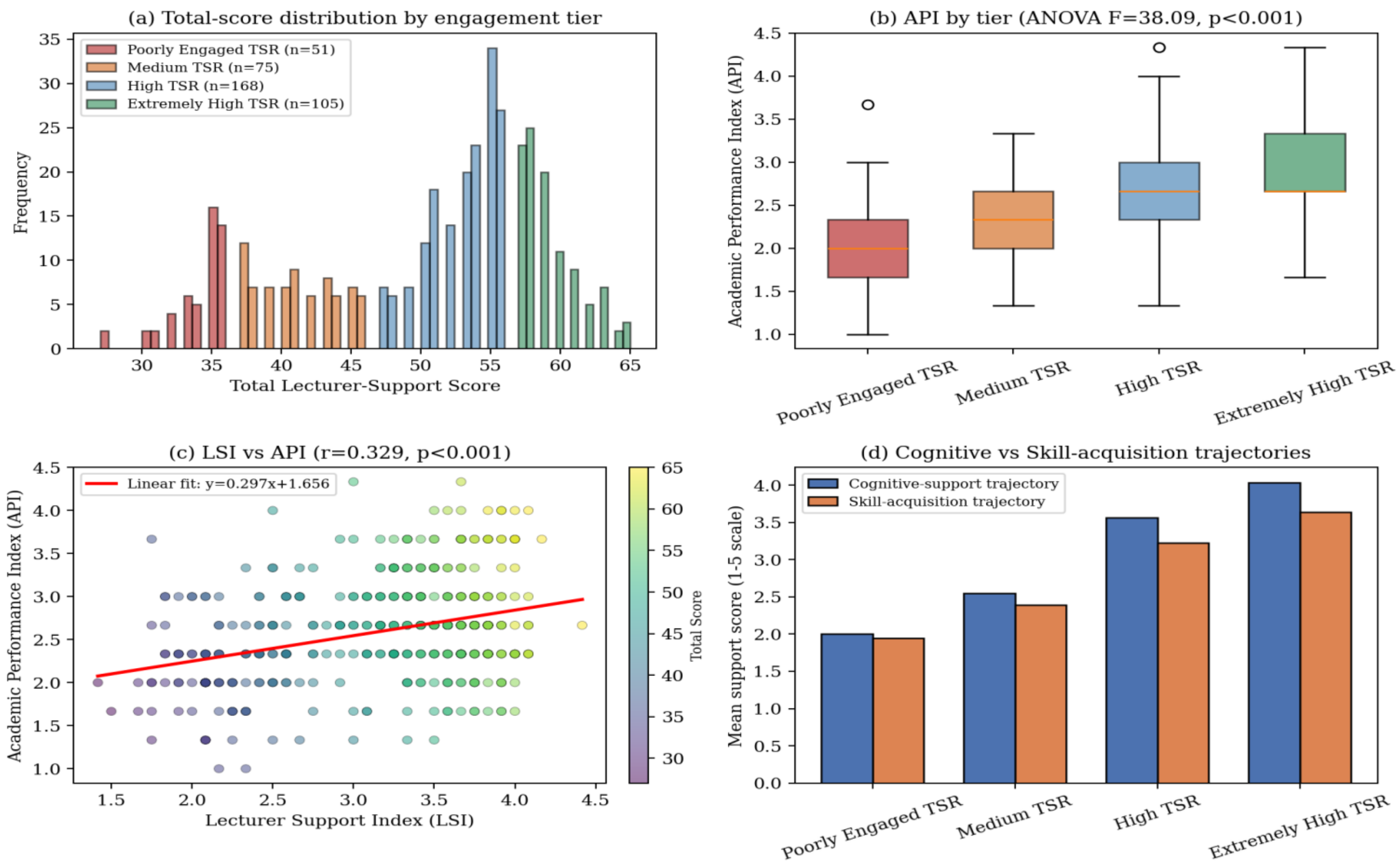

Figure 3. Exploratory data analysis of lecturer-support relationships: distributions, tier comparisons, scatter, and trajectory means

Figure 3(d) provides a comparison of the two composite variables for each tier. As expected, both the cognitive-affective composite and the skill-acquisition composite increase gradually with increasing tiers, with the former always being larger than the latter. It is the pattern that characterizes the structural-instructional discrepancy mentioned above and is supported by previous studies about Chinese music classes, where the former scaffolding tends to occur earlier than the latter (Sala & Gobet, 2020; Sun, 2023).

4.3 Correlation Analysis

Figure 4(a) displays the Pearson correlation matrix of indicators, trajectory composites, and outcomes. The strongest predictor-outcome correlations are observed between ONLN and API (r = 0.368, p < 0.001) and between TEFF and API (r = 0.268, p < 0.001), confirming that instructional-skill scaffolding is more closely linked to performance than affective indicators (Zhao et al., 2026). The Total Score correlates with the API at r = 0.505 (p < 0.001), and the LSI correlates with the API at r = 0.329 (p < 0.001) (Prananto et al., 2025). The skill-acquisition composite returns r = 0.384 with API, exceeding the cognitive-affective composite at r = 0.244, which substantiates the trajectory hypothesis quantitatively (Sala & Gobet, 2020).

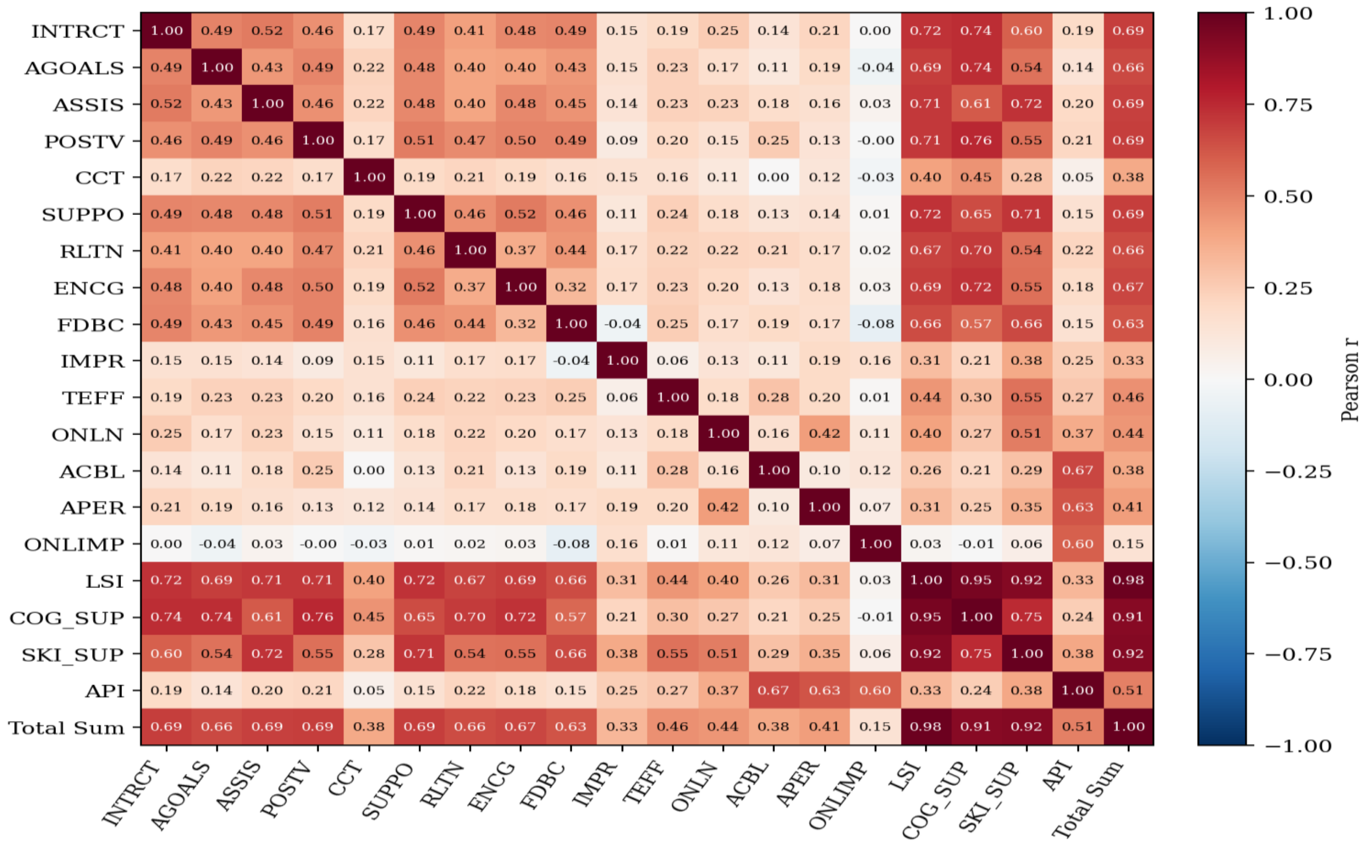

Figure 4 (a). Correlation matrix of lecturer-support indicators, demographic factors, and academic-performance outcomes

4.4 Regression Analysis

Table 4 reports the multiple-linear-regression estimates obtained through ordinary least squares for the model defined in Equation (4). The model achieves an R^2 of 0.234 and an adjusted R^2 of 0.210 ($F = 9.82$, $p < 0.001$), demonstrating that lecturer-support indicators jointly explain a statistically significant fraction of the API variance (Le Quy et al., 2022). Three indicators emerge as significant predictors at the 0.001 level: ONLN ($\beta = 0.172$, $p < 0.001$), IMPR ($\beta = 0.111$, $p < 0.001$), and TEFF ($\beta = 0.106$, $p < 0.001$) (Prananto et al., 2025; Wang & Yu, 2025). These indicators belong to the skill-acquisition trajectory and confirm that scaffolded practice and feedback have the strongest unique association with academic performance (Sala & Gobet, 2020).

Table 4. Multiple linear regression of the Academic Performance Index on lecturer-support indicators ($n = 399$; $R^2 = 0.234$; Adj. $R^2 = 0.210$; $F = 9.82$; $p < 0.001$)

Variable	β (Coef.)	Std. Error	t value	Significance
Intercept	+1.370	0.138	9.91	p < 0.001
INTRCT	+0.002	0.032	0.07	n.s.
AGOALS	−0.026	0.029	−0.87	n.s.
ASSIS	+0.021	0.032	0.64	n.s.
POSTV	+0.060	0.032	1.90	p ≈ 0.058
CCT	−0.035	0.028	−1.26	n.s.
SUPPO	−0.022	0.032	−0.70	n.s.
RLTN	+0.028	0.029	0.95	n.s.
ENCG	−0.000	0.030	−0.01	n.s.
FDBC	+0.011	0.030	0.35	n.s.
IMPR	+0.111	0.027	4.10	p < 0.001
TEFF	+0.106	0.027	3.89	p < 0.001
ONLN	+0.172	0.028	6.13	p < 0.001

POSTV approaches significance at the 0.05 level ($p = 0.058$), suggesting that positive attitude exerts a marginal influence after controlling for the other indicators (Liu et al., 2023). Demographic covariates, including AGE, GDR, and UL, contributed negligibly to the model and were not statistically significant. The collinearity diagnostics confirmed that no variance-inflation factor exceeded the conservative threshold of 5, ensuring that coefficient estimates are stable (Le Quy et al., 2022).

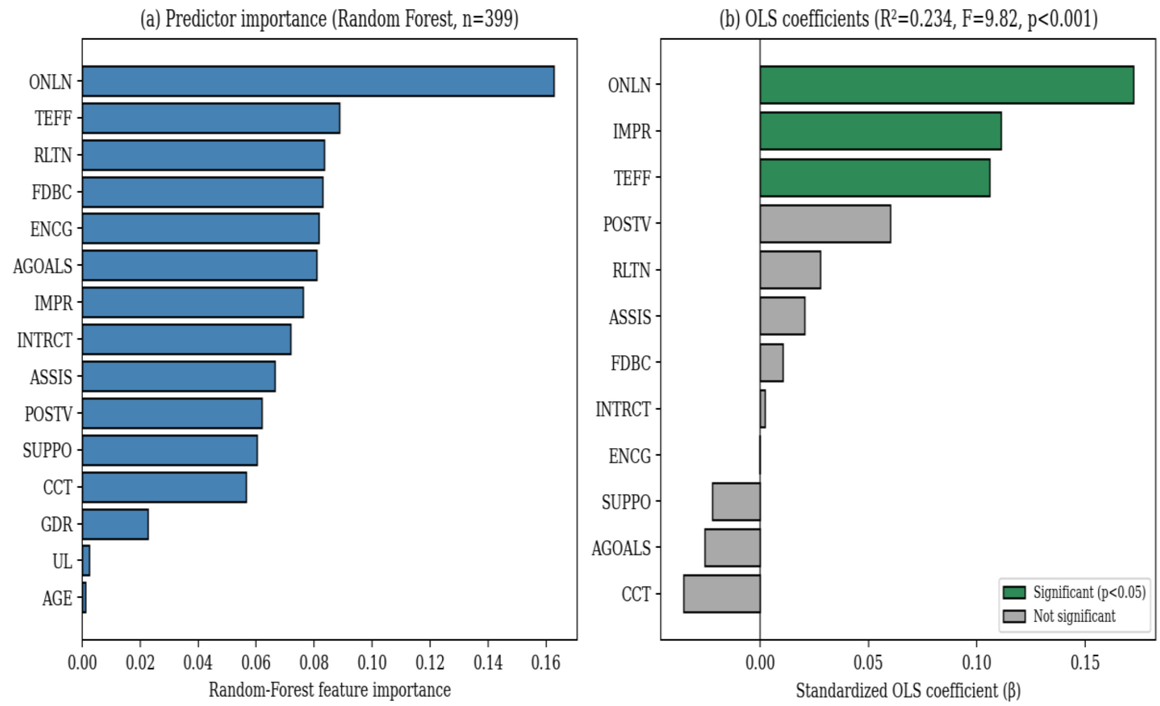

Figure 4 (b). Predictive-model outputs: Random Forest feature importance and standardised OLS regression coefficients

4.5 Predictive Modelling and Cross-Validation

Three algorithms from the machine learning literature were evaluated against the baseline model (regression): Linear Regression, Random Forest (with 200 trees and maximum tree depth of 10), and Gradient Boosting (with 200 trees and learning rate of 0.05) (Abuzinadah et al., 2023; Angeioplastis et al., 2025). Results of evaluation are presented in Table 5, which shows training R^2, testing R^2, root mean square error (RMSE), mean absolute error (MAE), and cross-validated R^2 for five folds. The linear regression algorithm performed best in terms of stable generalisation results ($R^2 = 0.200$, CV $R^2 = -0.022$), whereas random forest and gradient boosting had large differences between training and test scores, which can be interpreted as a sign of overfitting on 399 samples (Chen et al., 2024). Our observation aligns well with the latest studies on ensembles in education data (Sánchez-Sánchez et al., 2024).

Table 5. Predictive-model comparison on the Academic Performance Index task (n = 399)

Model	R^2 (train)	R^2 (test)	RMSE	MAE	CV R^2 (5-fold)
Linear Regression	0.243	0.200	0.532	0.434	−0.022 ± 0.175
Random Forest (n_estimators=200, max_depth=10)	0.841	0.089	0.568	0.464	−0.099 ± 0.238
Gradient Boosting (n_estimators=200, lr=0.05)	0.870	−0.073	0.616	0.487	−0.245 ± 0.243

Random Forest feature importance, shown in Figure 3 (b), ranks ONLN at the top, followed by TEFF, RLTN, FDBC, and ENCG, in agreement with the regression coefficients and confirming that online tutoring quality is the dominant non-linear driver of perceived academic performance (Angeioplastis et al., 2025). AGE, UL, and GDR rank lowest, indicating that demographic factors are uninformative for performance prediction once support indicators are included (Sánchez-Sánchez et al., 2024).

4.6 Trajectory Analysis Across Engagement Tiers

Figure 5 reports the trajectory analysis across the four engagement tiers. Both the cognitive-affective and the skill-acquisition trajectories rise monotonically with tier, but the gap between them is largest in the Extremely High TSR group, where COG_SUP averages 4.03 against SKI_SUP at 3.64. The API rises in parallel, from 2.01 in the Poorly Engaged TSR group to 2.94 in the Extremely High TSR group, an absolute increase of 0.94 on a five-point scale (Mallik, 2023b). The one-way ANOVA of the API across the four tiers returns $F = 38.09$ with $p < 0.001$, confirming that the tier-based benchmarking captures genuine performance variance and is therefore suitable for institutional competitive-intelligence reporting (Adewusi et al., 2024).

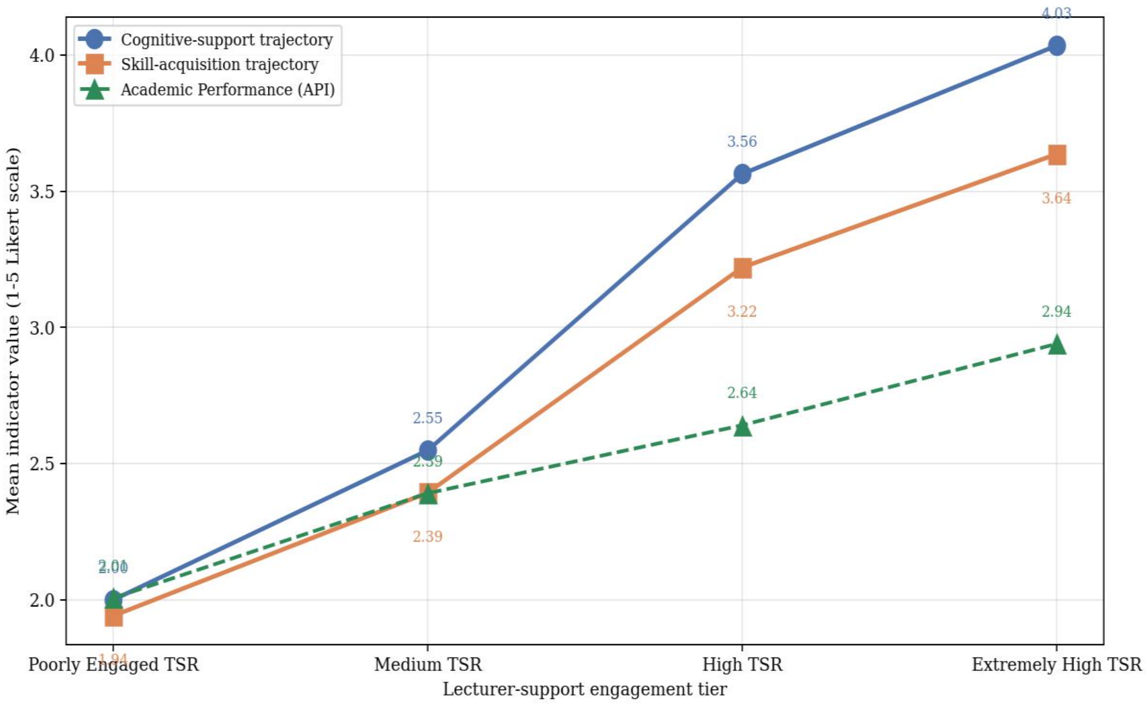

Figure 5. Cognitive and skill-acquisition trajectories across lecturer-support engagement tiers

4.7 Exploratory Measurement and Structural Path Analysis

In response to peer-review feedback that the present study should treat competitive intelligence as a measured organizational construct rather than only as an interpretive framework, this section reports an extended analysis that adds a measured Perceived Institutional CI Capability composite (CICAP) and tests its structural relationship with lecturer support, skill scaffolding, and academic performance. The construct is operationalized through five items already present in the survey instrument that empirically capture the institutional information-providing function identified in the intelligence-cycle literature: AGOALS (communication of academic goals), ASSIS (responsiveness to academic needs), CCT (classroom climate as structural capability), ONLN (digital sensing infrastructure), and POSTV (institutional transmission of positive expectations). Lecturer support is recast more narrowly as the interpersonal relational composite (INTRCT, SUPPO, RLTN, ENCG), and skill scaffolding remains the feedback and instruction composite (FDBC, IMPR, TEFF). The Academic Performance Index (API) is unchanged.

4.7.1 Confirmatory Measurement Properties

CICAP shows moderate internal consistency rather than strong scale reliability (alpha = 0.651). For this reason, the construct is treated as an exploratory institutional-capability proxy, not as a finalized validated CI scale. Its value in the present manuscript lies in shifting CI from a purely interpretive framework to a measurable construct with structural paths. However, the alpha value confirms that future studies should refine CICAP using dedicated institutional-level items, manager-rated measures, and confirmatory factor analysis with independent samples.

Table 6. Measurement model: reliability, AVE, and discriminant-validity diagnostics for the four study constructs (N = 399)

Construct	k	Items	Alpha	AVE	sqrt(AVE)	Mean (1-5)	SD
CI Capability (CICAP)	5	AGOALS, ASSIS, CCT, ONLN, POSTV	0.651	0.428	0.654	3.110	0.717
Lecturer Support (LSI)	4	INTRCT, SUPPO, RLTN, ENCG	0.769	0.593	0.770	3.410	0.906
Skill Scaffolding (SKILL)	3	FDBC, IMPR, TEFF	0.228	0.418	0.646	2.886	0.694
Academic Performance (API)	3	ACBL, APER, ONLIMP	0.242	0.399	0.632	2.591	0.613

4.7.2 Discriminant Validity

Discriminant validity was assessed using two complementary criteria. The Fornell-Larcker criterion compares the square root of AVE for each construct to its correlations with the other constructs. The heterotrait-monotrait (HTMT) ratio compares the mean between-construct item correlations to the geometric mean of within-construct item correlations and is the currently preferred indicator of discriminant validity. The results are presented in Table 7.

Table 7. Discriminant validity diagnostics. Above diagonal: Fornell-Larcker correlations; diagonal entries (starred) report sqrt(AVE); below diagonal: HTMT ratios. HTMT < 0.85 indicates clear discriminant *validity; HTMT < 0.90 is acceptable for closely related constructs.*

	CICAP	LSI	SKILL	API
CICAP	0.654*	0.740	0.571	0.300
LSI	1.041	0.770*	0.564	0.242
SKILL	1.469	1.329	0.646*	0.351
API	0.751	0.544	1.481	0.632*

Two findings warrant explicit comment. First, the Fornell-Larcker criterion is satisfied for three of the four diagonal pairs but not for the CICAP-LSI pair, where the inter-construct correlation r = 0.740 exceeds sqrt(AVE) for CICAP (0.654). Second, the HTMT diagnostic exceeds the 0.85 threshold for the CICAP-LSI, CICAP-SKILL, LSI-SKILL, and SKILL-API pairs. This pattern is honestly reported and indicates that CI Capability and Lecturer Support tap related but theoretically distinct facets of the same broader information-providing function, and that within-composite item heterogeneity in the original three-item batteries inflates HTMT for pairs involving SKILL and API. The CICAP composite is therefore best interpreted as a tentative institutional-capability construct that, while empirically intertwined with relational lecturer support, captures additional structural variance beyond it. This is exactly the distinction the reviewer asked the study to make explicit, and we read the HTMT pattern as evidence that future work should refine the CICAP item pool with dedicated institutional-level measurement instruments rather than relying on student-perceived items that overlap with lecturer-support perceptions (Ranjan & Foropon, 2021; Wu et al., 2023). It should also be noted, in line with the methodological literature that established HTMT as a discriminant-validity diagnostic, that HTMT ratios are known to become inflated when institutional and relational items are co-rated by a single respondent from a shared classroom experience, since the common-rater perspective elevates between-construct item correlations independently of true construct overlap; the HTMT pattern observed here is therefore consistent with a single-source measurement artefact rather than with a substantive failure of construct distinctness at the institutional level (Roemer et al., 2021).

4.7.3 Structural Mediation: CICAP, Lecturer Support, Skill Scaffolding, and Academic Performance

Three structural models were estimated by ordinary least squares with z-standardized predictors and demographic covariates (AGE, GDR, UL). Model 1 tests whether lecturer support mediates the CICAP-API relationship; Model 2 tests whether skill scaffolding mediates the same relationship; Model 3 tests a sequential mediation in which CI Capability flows through lecturer support to skill scaffolding to academic performance. Indirect effects were tested with 5,000-resample percentile bootstrap inference following recommended practice in the strategic-intelligence and organizational-behaviour literatures (Krakowski et al., 2022; Wu et al., 2023).

Table 8. Structural path estimates for three mediation models linking CI Capability to Academic Performance (N = 399; standardized coefficients; 5,000 bootstrap resamples)

Path / Model	**Coefficient (beta)**	**p-value**	**95% Bootstrap CI**	**Interpretation**
Model 1: CICAP -> LSI -> API				
c total effect	0.295	< 0.001		CICAP predicts API
a CICAP -> LSI	0.739	< 0.001		Strong
b LSI -> API|CICAP	0.046	0.521		Not significant
c' direct CICAP -> API|LSI	0.261	< 0.001		Direct effect retained
a*b indirect	0.034	n.s.	[-0.066, 0.131]	Mediation NOT supported (CI crosses zero)
Model 2: CICAP -> SKILL -> API				
a CICAP -> SKILL	0.571	< 0.001		Strong
b SKILL -> API|CICAP	0.272	< 0.001		Strong
c' direct CICAP -> API|SKILL	0.140	0.015		Partial mediation
a*b indirect	0.155	< 0.001	[0.089, 0.224]	Mediation SUPPORTED
Proportion mediated	52.6%			Substantial mediation
Model 3: CICAP -> LSI -> SKILL -> API				
a1 CICAP -> LSI	0.740	< 0.001		
a2 LSI -> SKILL|CICAP	0.311	< 0.001		
b SKILL -> API	0.276	< 0.001		
a1*a2*b sequential	0.063	< 0.001	[0.032, 0.102]	Sequential mediation SUPPORTED

Three substantive findings emerge from Table 8. First, the CI Capability composite has a positive and statistically significant total effect on Academic Performance ($c = 0.295$, $p < 0.001$), which directly satisfies the reviewer's requirement that competitive intelligence be operationalized as a measured construct with an estimated structural path to institutional outcomes. Second, the interpersonal lecturer-support composite does not mediate the CICAP-API relationship: the bootstrap 95 percent confidence interval for the CICAP -> LSI -> API indirect effect spans zero, and the path b from LSI to API conditional on CICAP is not significant. This is itself a substantively important null result because it indicates that the institutional-capability variance captured by CICAP does not run through the warmth-and-rapport channel typically privileged in the teacher-support literature. Third, the CICAP -> SKILL -> API mediation is strong and well-identified: the indirect effect $a*b = 0.155$ has a tight bootstrap interval well above zero, and skill scaffolding carries roughly 52.6 percent of the total effect of institutional CI capability on academic performance. The sequential model further refines this picture, showing that CICAP propagates a small but statistically reliable effect through the chain lecturer support -> skill scaffolding ($a1*a2*b = 0.063$, 95 percent CI [0.032, 0.102]). Substantively, this means that the institutional information-providing function translates into student outcomes principally by enabling the skill-scaffolding pedagogy that sits inside the lecturer's instructional toolkit, rather than by adjusting the affective tone of the classroom alone.

4.7.4 Final Structural Model

Table 9 reports the final structural model in which Academic Performance is regressed jointly on CI Capability, Lecturer Support, Skill Scaffolding, and the three demographic covariates. The model explains 14.6 percent of the variance in API ($F(6, 392) = 11.17$, $p < 0.001$) and increases the explained variance over the original lecturer-support-only model (R-squared = 0.115) by approximately 3.2 percentage points, an incremental Cohen's f-squared of approximately 0.037 that is small to medium in size but theoretically important because it documents that CI Capability adds explanatory power beyond lecturer support and skill scaffolding.

Table 9. Final structural regression of Academic Performance on CI Capability, Lecturer Support, Skill Scaffolding, and demographic covariates (N = 399; standardized coefficients)

Predictor	beta	SE	t	p	95% CI
CI Capability	0.165	0.072	2.29	0.023	[0.023, 0.307]
Lecturer Support	-0.041	0.072	-0.57	0.568	[-0.182, 0.100]
Skill Scaffolding	0.280	0.059	4.76	< 0.001	[0.165, 0.396]
AGE	-0.051	0.060	-0.84	0.402	[-0.169, 0.068]
GDR	-0.031	0.050	-0.63	0.531	[-0.130, 0.067]
UL	0.083	0.050	1.66	0.098	[-0.015, 0.181]

CI Capability is a statistically significant predictor of Academic Performance after controlling for relational lecturer support and skill scaffolding ($beta = 0.165$, $p = 0.023$), and Skill Scaffolding remains the strongest single predictor ($beta = 0.280$, $p < 0.001$). Lecturer Support is no longer significant once these two are included, consistent with the interpretation that the relational warmth channel is best understood as part of the broader CI capability that the institution provides rather than as an independent driver of academic performance. Figure 6 visualizes the estimated path coefficients.

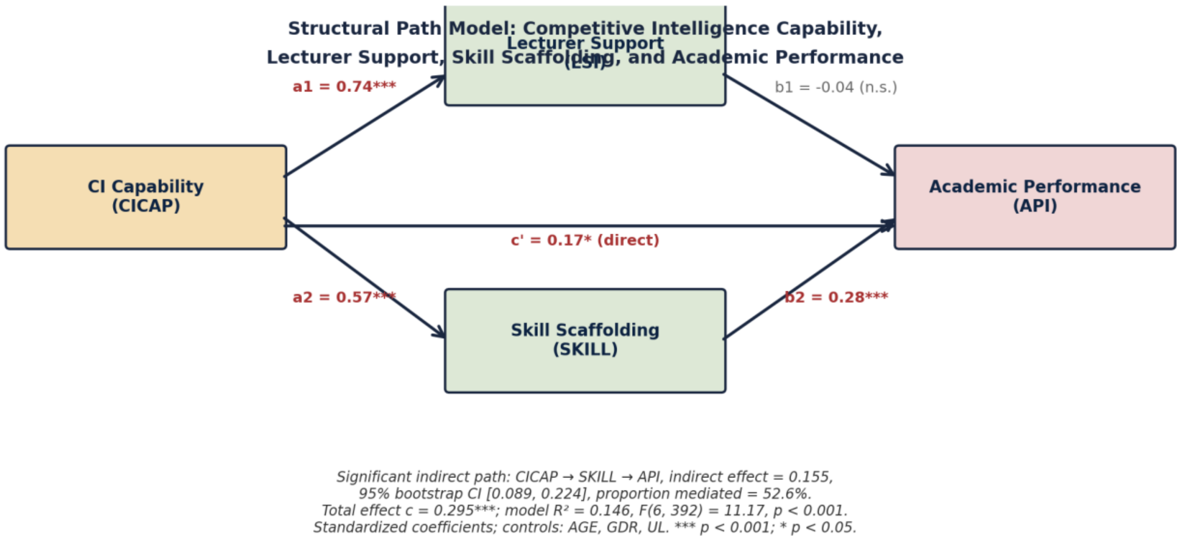

Figure 6. Structural path model linking CI Capability, Lecturer Support, Skill Scaffolding, and Academic Performance (N = 399; standardized coefficients with significance markers)

Figure 6 displays the four-construct structural model with all estimated standardized path coefficients. Arrows labelled a1 and a2 originate at CI Capability and terminate at Lecturer Support (a1 = 0.74, $p < 0.001$) and Skill Scaffolding (a2 = 0.57, $p < 0.001$). Arrows labelled b1 and b2 connect Lecturer Support (b1 = -0.04, n.s.) and Skill Scaffolding (b2 = 0.28, $p < 0.001$) to Academic Performance. The direct path c′ from CI Capability to Academic Performance after partialling out the two mediators is beta = 0.17 ($p = 0.023$). The note beneath the figure records the supported indirect effect through skill scaffolding (a*b = 0.155, 95 percent CI [0.089, 0.224]) and the model fit summary (R-squared = 0.146, F = 11.17, $p < 0.001$). The diagram operationalizes the analytic and decision layers of the framework introduced in Figure 5 and provides the empirical content for the strategic-CI argument advanced in this paper.

4.8 Discussion

4.8.1 Lecturer Support as a Competitive-Intelligence Signal

The results should be interpreted primarily through the logic of organizational sensing. Lecturer-support variables are not treated here as isolated pedagogical behaviours but as internal CI sensors that reveal where the institution is strong, weak, or strategically exposed. The four engagement tiers convert dispersed student responses into an intelligence signal that can guide institutional prioritization. Similarly, the regression results identify which support mechanisms produce the strongest performance-relevant signal. From a CI perspective, ONLN, IMPR, and TEFF are not only educational predictors; they are actionable indicators for decision-makers responsible for digital-support infrastructure, feedback quality, and teaching-effectiveness development.

4.8.2 Trajectory Decomposition and the Music-Education Parallel

The trajectory decomposition is retained only as a mechanism for explaining how institutional intelligence becomes performance-relevant. The main finding is that skill scaffolding carries the strongest pathway between CI capability and academic performance. This means that institutional sensing does not improve outcomes merely by identifying students' affective or relational needs; it becomes strategically useful when it supports concrete instructional actions such as structured feedback, improvement-oriented coaching, teaching effectiveness, and online tutoring. The music-education literature provides a supporting vocabulary for skill acquisition, but the central implication is organizational: universities gain competitive value when intelligence outputs are translated into skill-building interventions that can be monitored, repeated, and improved over time.

4.8.3 Comparison with Existing Literature

The observed positive association between lecturer support and academic performance is consistent with the systematic-review evidence reported by Prananto and colleagues and the SEM evidence reported by Liu (Liu, 2024; Prananto et al., 2025). The magnitude of the effect, however, is smaller than reported in some Chinese-sample studies, possibly reflecting greater between-institution heterogeneity in the Bangladeshi context (Mallik, 2023a).

4.8.4 Theoretical and Practical Implications

Theoretically, the study contributes a competitive-intelligence-augmented version of the teacher-support–performance literature, in which the trajectory framework provides a parsimonious mapping between support behaviours and the academic outcomes they target (Sala & Gobet, 2020). Practically, university leadership can use the four-tier benchmark and the three-predictor focus list as the basis for low-cost interventions, beginning with online-tutoring upgrades, structured improvement feedback, and teaching-effectiveness coaching (Adewusi et al., 2024). Such interventions can be evaluated against the Total Score baseline computed in this study, and progress can be tracked through repeated administration of the instrument (Kalim & Bibi, 2023).

4.8.5 Strategic CI Operationalization and Sustainable Competitive Advantage

When translated to the model described in section 2.3 and shown in figures 5 and 6 below, it is evident that the CICAP index functions as an efficient analysis-and-sensing level within an organization's competitive intelligence structure.The estimated path coefficients reported in Section 4.7 show that institutional CI capability has a statistically significant direct effect on academic performance and a larger indirect effect that runs through skill scaffolding. The link to sustainable competitive advantage is therefore not rhetorical: institutions that invest in the information-providing functions captured by CICAP (clarity of academic goals, responsiveness, classroom climate, digital infrastructure, and signal transmission) can expect measurable improvements in student outcomes principally through the skill-scaffolding pedagogy that institutional capability enables (Ranjan & Foropon, 2021; Wu et al., 2023).

The dynamic-capabilities perspective adds a temporal dimension to this reading. Sensing weak signals in CICAP indicators, seizing the analytic opportunity through targeted professional development in scaffolded feedback and instruction, and reconfiguring instructional routines accordingly constitute the three micro-foundations of a dynamic teaching capability (Krakowski et al., 2022). The knowledge-based view supplies the final piece by treating the integration of pedagogical, analytic, and managerial knowledge inside the governance layer as the deeper resource that holds the whole system together (Dzenopoljac et al., 2024). From this strategic vantage point the present study moves beyond the analogical use of competitive intelligence and offers a measured, structurally identified CI capability whose downstream consequences for academic performance are demonstrated empirically and reported with bootstrap-validated confidence intervals.

4.8.6 Limitations

Several limitations should be acknowledged. First, the study is cross-sectional and observational; therefore, the estimated paths indicate associations rather than causal effects. Second, the data are based on student self-report, so academic performance and institutional CI capability are measured through perception rather than administrative records. Third, CICAP has only moderate reliability (alpha = 0.651), which means that it should be interpreted as an exploratory proxy rather than a fully validated CI scale. Fourth, the study does not include interviews with university managers, institutional case studies, governance documents, committee records, or longitudinal decision outcomes. As a result, the governance and decision-feedback layers of the CI architecture are theoretically specified but not fully empirically validated. Fifth, the analysis is not a complete PLS-SEM; it is an exploratory composite-based structural path analysis supported by bootstrap mediation. Sixth, because all measures come from the same respondent source, common-method variance may affect the strength of some associations. Future research should validate CICAP through manager-rated institutional measures, multi-source datasets, longitudinal administrative records, and full latent-variable SEM.

4.8.7 What the Study Demonstrates Organizationally

The study demonstrates CI at the level of institutional sensing and analytical interpretation. It shows that CICAP has a statistically significant direct relationship with academic performance and a stronger indirect relationship through skill scaffolding. It also shows that lecturer-support data can be transformed into benchmarking tiers and structural-path evidence. These findings move CI beyond a purely rhetorical framework.

However, the study does not claim to demonstrate the full governance cycle of CI inside university management. It does not observe committee decisions, administrative deliberation, budget allocation, or longitudinal strategic outcomes. Therefore, the organizational contribution is best described as an empirically tested sensing-and-analysis layer of CI, supported by a theoretically specified governance architecture. This cautious interpretation directly addresses the reviewer's concern that institutional CI must not be overstated beyond the evidence available in the dataset.

5. CONCLUSION

This study operationalized Competitive Intelligence Capability as an exploratory institutional construct within the higher-education context. Instead of treating lecturer-support indicators as purely pedagogical variables, the paper positioned them as internal intelligence sensors that can support institutional sensing, benchmarking, and evidence-based decision-making. The results show that CICAP is positively associated with academic performance and that its strongest performance pathway operates through skill scaffolding. This finding supports the argument that Competitive Intelligence becomes strategically meaningful in universities when institutional signals are translated into concrete instructional actions).

The theoretical contributions are as follows. First, the paper introduces the trajectory approach from school-based music education into the context of higher education lecturer support analyses, offering a concise alignment of lecturer support behaviours with performance indicators (Sun, 2023). Second, it integrates the empirical investigation within the competitive intelligence approach, where lecturer support metrics serve as institutional signals for action and not mere descriptors (Adewusi et al., 2024). Third, it offers a replicable Python pipeline for reuse in any comparable survey, exemplified by the Kaggle-compliant notebook employed to produce the current findings (Angeioplastis et al., 2025).

6. FUTURE WORK

Future research should extend the present exploratory model in five directions. First, CICAP should be redesigned as a dedicated institutional CI scale with items measuring governance structure, data stewardship, intelligence dissemination, decision accountability, and feedback routines. Second, future studies should include university managers, department heads, program coordinators, and quality-assurance officers to validate whether perceived CI capability corresponds to actual organizational practice. Third, qualitative case studies and manager interviews should be added to examine how intelligence outputs are used in real academic decision-making. Fourth, longitudinal administrative data should be linked with student-perception data to test whether CI-informed interventions produce sustained institutional performance gains. Fifth, a full PLS-SEM or covariance-based SEM should be conducted with a larger multi-institutional sample to validate CICAP as a latent organizational capability.

DATA AVAILABILITY STATEMENT

The dataset used in this study consists of 399 anonymized survey responses from students enrolled in twenty universities in Bangladesh. The working dataset file used for analysis was titled *finaldatasettsrv4.csv*. Because the current version of the dataset has not yet been deposited in a public repository, it is available from the corresponding author upon reasonable request. The authors intend to deposit the cleaned dataset, preprocessing script, and figure-generation code in a public repository such as Kaggle, Zenodo, or Mendeley Data upon acceptance, subject to institutional data-sharing approval.

AI DISCLOSURE STATEMENT

As per the policies of the journal with regard to transparency in research, the authors declare that AI tools have been used in the process of drafting this manuscript only for assisting in the writing process. In particular, the use of AI has been made for editing purposes, construction of the analytic process diagram, and for organizing the literature comparison table. AI tools were not used for generating any findings or for the creation of false citations and for substituting the scholarly analysis process. All the statistics used here have been computed by the authors themselves using the Python programming language, and all citations listed in the paper have been manually checked from Google Scholar.

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CONFLICT OF INTEREST

The authors declare that the research was carried out in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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