

From Learning Analytics to Action: An Integrated MTSS Framework for College and Career Readiness in Digital Higher Education

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ABSTRACT:

Digital learning environments generate extensive evidence about participation, performance and interaction, learning analytics does not clearly define how this evidence should be used to provide differentiated support to the institution. This conceptual-methodological study proposes a multi-tiered system of support (MTSS) framework for college and career readiness (CCR) in digital higher education that is supported by learning analytics. The framework is grounded in learning analytics, MTSS, CCR, and self-determination theory, and connects approved data collection, indicators that are interpretable, professional review, tier assignment, intervention delivery, progress monitoring, and recalibration. A public dataset with 14,003 records is only used as a measurement-adequacy demonstration as it lacks direct measures of analytics exposure, MTSS delivery, validated engagement, and multidimensional CCR. No significant associations with examination performance were found with equal-weight or alternative-weight proxy summaries, and principal-component diagnostics indicated poor dimensional coherence. These results do not confirm or disconfirm the proposed relationships, but rather indicate that construct misalignment cannot be overcome by large samples and reproducible analysis. The study presents an operational workflow of analytics-to-action, governance and intervention needs, conceptual propositions for future testing and a construct aligned data specification for a potential institutional pilot.

Implications for Practice or Policy

- The use of analytics alerts should be viewed as a call to action for professional review, not as automatic tier assignments.
- Intervention type, dosage, fidelity, uptake and response should be documented for intervention across MTSS tiers by faculty and support teams.
- The researchers should test the framework over time with direct measures of analytics exposure, student engagement and multidimensional CCR.

Keywords: learning analytics; multi-tiered system of support; college and career readiness; digital higher education; conceptual framework; measurement adequacy

1. Introduction

The use of digital technologies has significantly revolutionized higher education, with the use of learning management systems (LMSs), massive open online courses, online assessment platforms, and virtual collaboration environments. These spaces not only offer more ways for teaching and learning to take place, they also provide a wealth of information about student engagement, participation, academic performance and skill acquisition. With responsible analysis, these data can be used to inform evidence-based decisions that aim to enhance learning processes and student outcomes (Siemens & Baker, 2012). Higher education institutions will also be expected to equip students with the skills needed for academic advancement and job opportunities. College and Career Readiness (CCR) thus includes academic content and the critical thinking, communication, collaboration, problem-solving, and transition-related skills and competencies needed for success in college and careers (Conley, 2014; Morningstar et al., 2017).

Although CCR is becoming more important, in many schools instruction and support focus mainly on the content and periodical evaluation. These strategies may not be sufficient to meet the needs of students in terms of their learning needs, levels of engagement, and readiness for the workplace. Learning analytics, on the other hand, provides a complementary view to learning analytics by measuring, collecting, analysing and reporting data on the learner and their context to understand and enhance learning processes (Siemens & Baker, 2012). Analytics can be used to track participation, to identify early warning signs and patterns that may indicate academic struggles or disengagement. However, its educational value is contingent on the follow-up actions that are taken in response to the findings and are timely and appropriate (Ifenthaler & Yau, 2020).

Learning analytics can identify patterns of behaviour and performance, but it does not by itself specify how institutions should differentiate interventions. The Multi-Tiered System of Support (MTSS) provides a structured approach in which the intensity of assistance is matched to student need through universal, targeted, and intensive levels of support (Fuchs & Fuchs, 2006; McIntosh & Goodman, 2016). Tier 1 provides universal supports for all students, Tier 2 provides targeted assistance for students who do not respond adequately to universal provision, and Tier 3 provides intensive and individualised support for students with persistent or complex needs. Integrating analytics with this tiered structure can enable earlier identification, systematic intervention selection, and continuous progress monitoring.

Accordingly, this study develops an integrated Learning Analytics-Driven MTSS framework for supporting college and career readiness in digital classrooms. It seeks to (a) specify how directly measured analytics exposure and student indicators can inform professionally reviewed tiered-support decisions, (b) define an operational workflow for implementation and continuous evaluation in higher education, and (c) use a public secondary dataset to demonstrate the risks of construct misalignment and arbitrary proxy construction. The empirical component is not a test of an implemented MTSS programme or multidimensional CCR because the dataset contains neither intervention records nor career-readiness outcomes. The remainder of the paper summarizes the existing literature and theoretical background, introduces the framework and conceptual propositions, describes the demonstration of the measurement, outlines the implementation model, and discusses the needs for the purpose-designed institutional validation.

2. Literature Review

2.1 Digital Transformation and Data-Driven Education

Digital transformation in higher education is not just about the use of learning management systems (LMS), artificial intelligence (AI), and analytics platforms. It also necessitates pedagogical and organisational redesign in order to enable the use of learner-interaction data to support transparent and educationally meaningful decisions (Gasevic et al., 2019; Holmes et al., 2019). The value of analytics is dependent on governance, interpretability, staff capability and the existence of appropriate support responses, but can be used to support cohort monitoring, early identification, adaptive feedback and institutional planning.

Dashboards and predictive systems can provide a summary of participation, assessment and behavioural indicators for the teacher and administrator. However, reviews reveal that the field has been more focused on data collection and prediction than in showing evidence of enhanced teaching and learning (Ifenthaler & Yau, 2020; Viberg et al., 2018). This actionability gap encourages a framework that begins with an analytics alert that triggers professional inquiry and multiple levels of support rather than an automatic assessment of the student.

2.2 Learning Analytics to Support Student Success

Learning analytics has evolved from descriptive reporting to predictive and prescriptive analytics aimed at detecting risk and suggesting potential educational interventions. Common applications include digital traces, assessment performance, participation, and resource use, for advising, course improvement, and retention (Hernandez-de-Menendez et al., 2022; Rakovic et al., 2023). But just because the variables selected are accurate predictors does not mean they are indicators of engagement, support received, or career readiness, nor does it mean that they dictate the intervention that should be undertaken after an alert is issued.

The main challenge is to translate the identified need, as a product of analysis, into an accountable educational action. Explicit decision rules, professional review, documentation of interventions, student involvement, and progress monitoring are needed in institutions. The use of learning analytics should not be considered as a standalone predictor, but as another part of a socio-technical support system (Ferguson, 2012; Gasevic et al., 2019; Ifenthaler & Yau, 2020).

2.3 Multi-Tiered Systems of Support in Education

A multi-tiered system of support (MTSS) is a prevention-based approach to academic and behavioural support that takes into account student needs. Tier 1: Universal provision for all students, Tier 2: Additional provision for students who need more than universal provision, Tier 3: Intensive individualised provision for persistent and/or complex needs. The framework focuses on data-informed decision making, evidence-based intervention, and continuous progress monitoring (Fuchs & Fuchs, 2006; McIntosh & Goodman, 2016).

MTSS has also been proposed as a way to help students make the transition from school to college and/or careers. D'Souza et al. (2020) believe that structured academic and behavioural supports have the potential to help develop college and career readiness competencies. In digital learning spaces, real-time data on attendance, engagement, assignment completion, and performance can help teachers identify students in need of extra support. However, the use of analytics indicators should be used as a guide to professional judgment and not as a classification or punishment.

2.4 College and Career Readiness in Digital Higher Education

College and career readiness (CCR) is the knowledge, strategies, skills and transition competencies needed for success in college and career. It is not just about academic performance, but also about critical thinking, communication, collaboration, problem solving, adaptability, digital literacy and career self-management

(Conley, 2014; Morningstar et al., 2017). These skills also encompass responsible use of digital tools, interpretation of information, virtual collaboration and adapting to evolving professional needs in technology-rich environments.

Digital learning environments offer opportunities to observe participation and progression, but not participation and progression themselves are measures of readiness. Institutions need to link analytics indicators to concrete evidence of competency from projects, portfolios, internships, validated assessments, and transition outcomes. This is important because examination performance is a measure of just one aspect of CCR.

Learning analytics can be used in combination with structured mentoring and intervention to support the identification of competency gaps

and the provision of support to academic and professional-development pathways (Rakovic et al., 2023; Williamson, 2016). The role of analytics is not to replace the CCR assessment, but to identify students in a timely fashion who might need direct assessment and differentiated support.

The literature reviewed shows an increasing amount of interest in the fields of learning analytics, MTSS, student engagement, and CCR. These domains are generally studied separately, however: Learning Analytics studies focus on measurement and prediction, MTSS studies focus on differentiated intervention, and CCR studies focus on academic and employability competencies. Table 1 presents a synthesis of 12 studies that offer the main conceptual and empirical arguments for the integration proposed.

Table 1. Summary of Literature on Learning Analytics, MTSS, and College and Career Readiness

Author(s) and year	Area	Major contribution	Limitation	Relevance to this study
Ferguson (2012)	LA	Identified drivers, developments, and implementation challenges.	Did not specify a tiered intervention process.	Establishes the implementation context for analytics.
Siemens (2013)	LA	Positioned learning analytics as an emerging interdisciplinary field.	Focused on disciplinary development rather than intervention delivery.	Provides the conceptual foundation for the analytics layer.
Conley (2014)	CCR	Presented a multidimensional profile of college and career readiness.	Did not connect readiness with continuous digital monitoring.	Defines the principal readiness outcome domain.
McIntosh and Goodman (2016)	MTSS	Explained integrated tiered academic and behavioural support.	Primarily oriented toward school-level implementation.	Provides the structure for differentiated interventions.
D'Souza et al. (2020)	MTSS/CCR	Connected tiered support with college and career readiness.	Did not include real-time analytics or empirical testing.	Supports the conceptual integration of MTSS and CCR.
Viberg et al. (2018)	LA	Reviewed the higher-education learning analytics landscape.	Reported limited evidence that analytics directly improves learning.	Supports the need to translate analytics into action.
Holmes et al. (2019)	AI/education	Discussed AI-enabled personalization, assessment, and decision support.	Offered a broad AI perspective without an MTSS workflow.	Supports adaptive and personalised digital support.

Gašević et al. (2019)	LA adoption	Proposed a socio-technical approach to institutional adoption.	Did not operationalize dynamic tier assignment.	Informs governance and institutional implementation.
Ifenthaler and Yau (2020)	LA/study success	Systematically reviewed analytics for study success in higher education.	Found limited rigorous evidence linking analytics to interventions.	Supports early identification and evidence-informed support.
Caspari-Sadeghi (2023)	LA/assessment	Outlined monitoring, feedback, prediction, and intervention functions.	Did not integrate these functions with MTSS and CCR.	Links assessment analytics with intervention planning.
Chiu (2022)	SDT/engagement	Applied SDT to explain engagement in online learning.	Did not examine MTSS or career-readiness outcomes.	Supports the motivational pathway in the framework.
Raković et al. (2023)	LA/assessment	Identified opportunities and challenges at the intersection of analytics and assessment.	Focused on assessment rather than tiered support implementation.	Supports the use of analytics for fine-grained monitoring.

2.5 Theoretical Foundation: Self-Determination Theory

The proposed Learning Analytics–Driven Multi-Tiered System of Support (MTSS) framework is conceptually rooted in the Self-Determination Theory (SDT) which focuses on the importance of motivation, autonomy, competence, and relatedness in the facilitation of effective learning experiences and positive educational outcomes. According to SDT by Deci and Ryan (2000), students will be more active, persistent and successful in learning when the learning environment meets their psychological and developmental needs. The theory has been extensively used in the study of student motivation, self-regulated learning, engagement, and academic achievement in technology-supported learning environments in higher education.

The proposed integration aligns with the core principles of self-determination theory. Analytics-supported feedback may strengthen perceived competence when it helps students identify attainable next steps, while differentiated MTSS interventions may strengthen relatedness through mentoring and meaningful educator interaction. These benefits depend on how the

technology and support are designed; opaque surveillance, deficit labelling, or automated escalation could undermine autonomy and trust.

Analytics-informed support may also promote autonomy when students can view, discuss, and act on their own learning information. Research grounded in self-determination theory associates autonomy support, competence, and relatedness with motivation, engagement, self-regulated learning, and persistence in digitally mediated contexts (Chiu, 2022; Ryan & Deci, 2020). SDT therefore provides an explanatory lens for the framework's proposed motivational pathway, but that pathway requires direct measurement in a prospective institutional study.

3. Research Gap and Contribution

Learning analytics provides institutions with methods for collecting and interpreting data on participation, engagement, performance, and learning behaviour. MTSS, by contrast, provides a structured process for differentiating the intensity of support according to student need. Both approaches are based on data-informed decision making and progress monitoring, but have tended to be separate streams of research and practice. While learning analytics studies

often conclude with prediction or visualization, MTSS studies are usually initiated by a need and intervention delivery is the point of focus.

This separation results in an important research gap. Analytics can signal a student as being disengaged, or academically at risk, but not necessarily who should intervene, what intervention should be, when it needs to be escalated, or how it should be measured for improvement. Conversely, MTSS implementation may rely on periodic assessments and professional observation without fully using the continuous behavioural evidence generated in digital classrooms. CCR research adds a further requirement because institutions must support not only academic performance but also competencies associated with postsecondary transition and employability.

The present study addresses this gap by positioning learning analytics as the data-intelligence layer of an MTSS framework and linking professionally reviewed tiered interventions to academic progress and CCR development. The model specifies how learner data can be converted into interpretable indicators, reviewed in context, connected to support intensity, and evaluated through a closed feedback loop. It also addresses a methodological gap: conceptual frameworks are frequently paired with convenient secondary variables that do not directly measure the constructs or interventions under examination. A defensible test therefore requires direct measures of analytics exposure, actual MTSS assignment and dosage, validated engagement, and multidimensional CCR outcomes. The secondary-data analysis demonstrates this construct-alignment requirement; it is not presented as empirical validation. The paper has three contributions: it combines learning analytics, MTSS, CCR, and self-determination theory within a human reviewed analytics-to-action architecture; it translates the architecture into an operational implementation workflow; and it identifies the measurement and data needs for a potential institutional pilot.

4. Conceptual Development Approach

Theory-synthesis and model-development approach to conceptual scholarship (Jaakkola, 2020) is used in this study. The development process involved five steps: defining the actionability gap between learning analytics and student support; identifying learning analytics, MTSS, CCR, and self-determination theory as complementary domains; outlining construct boundaries; establishing the domains within an operational architecture connecting data, professional review, tiered intervention, and feedback; and identifying propositions and data requirements for future empirical testing. The aim was not to systematically review and estimate pooled effects, but to develop a coherent and feasible model, with explicit assumptions and measurement needs. The purpose was not to conduct a systematic review or estimate pooled effects, but to produce a logically coherent and implementable model whose assumptions and measurement requirements are explicit.

The framework's internal coherence was examined by mapping each proposed relationship to a directly observable variable and an institutional decision process. The public dataset was then used as a negative-case measurement demonstration: it shows how apparently relevant behavioural variables can fail to represent analytics exposure, MTSS delivery, validated engagement, or CCR. The use of secondary data is therefore methodological rather than confirmatory.

5. Proposed Analytics-Driven MTSS Framework

5.1 Framework Architecture and Tiered Support

Digital learning environments provide institutions with opportunities to use learner data for timely support, while MTSS provides a structured process for differentiating the intensity of that support. The proposed framework connects governed data collection and interpretable analytics to professional review, Tier 1 universal provision, Tier 2 targeted intervention, Tier 3 intensive individualised

support, documented delivery, and continuous outcome monitoring. CCR is the intended multidimensional outcome domain and must be measured directly through academic,

employability, transition, project, internship, and career-related evidence. Figure 1 presents the analytics-to-action architecture.

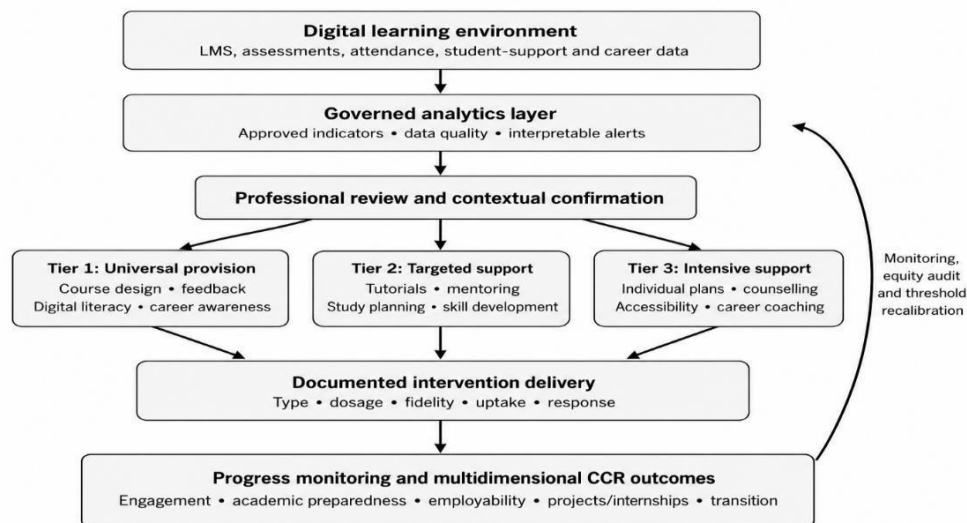


Figure 1. Analytics-to-action learning analytics-driven MTSS framework for college and career readiness

The basis for the proposed framework is the idea that data created by students using online learning systems (e.g., Learning Management Systems) can be systematically reviewed in order to identify their learning patterns, the extent to which they are engaged in their studies, and any elements that may put the student at risk for failure. By analysing these insights, targeted interventions on each level of the MTSS model can be developed. By combining data-driven analytics with structured methods of providing intervention supports, educational institutions can have the beginning of a proactive approach to supporting students in achieving both academic success and the readiness for a career. Learning analytics is the layer of data intelligence for this entire framework and provides an information source that can come from any number of sources, including the Learning Management Systems used by students, online assessments, discussion forums, and other forms of interactive learning tools. All of these data collection sources ensure that educators are able to use critical data indicators including student participation, assessment success, skill development, and engagement patterns to track overall performance levels and identify students

needing either academic or career pathway assistance. The MTSS portion of the overall Framework includes a process to use insights derived from analytical processes to develop interventions for providing assistance to at-risk students. The framework arranges interventions according to three consecutive levels of support so that students can be supported according to their personal learning needs.

At Tier 1, all students receive universal access to clearly structured course materials, orientation to digital learning tools, foundational digital-literacy support, formative feedback, and career-awareness resources. Learning analytics is used to monitor cohort-level participation and identify early signs of disengagement without labelling students as deficient.

At Tier 2, students displaying moderate academic or engagement difficulties receive targeted support. Indicators may include declining performance, irregular participation, incomplete assignments, or reduced interaction with learning resources. Appropriate interventions include small-group mentoring, supplemental tutorials, academic workshops, study-planning assistance, and targeted career-skill development.

At Tier 3, students who have ongoing and/or significant academic, engagement or readiness needs are provided with intensive one-to-one support. Interventions include one-to-one mentoring, individual academic planning, career referrals, accessibility support, intensive skills coaching and coordinated career support, following review by faculty members and appropriate support professionals. Predictive indicators can be used to guide the review, but professional judgment and documented student circumstances will be the final factors.

The combination of learning analytics and MTSS allows institutions to move beyond a fragmented approach to support and largely react to student behaviour to a coordinated process guided by data. Real-time indicators can inform professional review, intervention selection, and progress monitoring, across the three tiers, leading to more timely and consistent student support. This model is integrated, and helps to create a more holistic learning experience that supports academic success and career readiness.

Table 2. Comparison of Traditional CCR Support and Data-Driven Support Systems

Dimension	Traditional CCR Support Approaches	Data-Driven Support Systems
Student Assessment	Periodic examinations and standardised testing	Continuous monitoring using learning analytics
Identification of Student Needs	Teacher observations and manual evaluations	Predictive analytics and real-time engagement tracking
Intervention Strategies	General academic counselling and remedial classes	Tiered interventions through MTSS frameworks
Personalization of Learning	Limited personalization due to large class sizes	Adaptive learning and personalised academic support
Career Readiness Development	Career guidance sessions and workshops	Data-informed career pathway recommendations
Decision-Making	Based on institutional experience and manual reporting	Evidence-based decisions supported by analytics dashboards

The framework is conceptual and implementation-oriented. Its relationships should be evaluated prospectively with construct-aligned institutional data rather than inferred from convenient behavioural proxies. The following propositions specify the relationships that require future validation.

5.2 Conceptual Propositions for Future Institutional Validation

P1: Directly measured exposure to actionable learning-analytics feedback is positively associated with student engagement measured using a validated instrument.

P2: Analytics-informed identification and professional review are positively associated with timely and appropriately differentiated MTSS intervention delivery.

P3: Documented MTSS intervention assignment, type, dosage, and response are positively associated with multidimensional college and career readiness outcomes.

P4: Validated student engagement is positively associated with multidimensional college and career readiness outcomes.

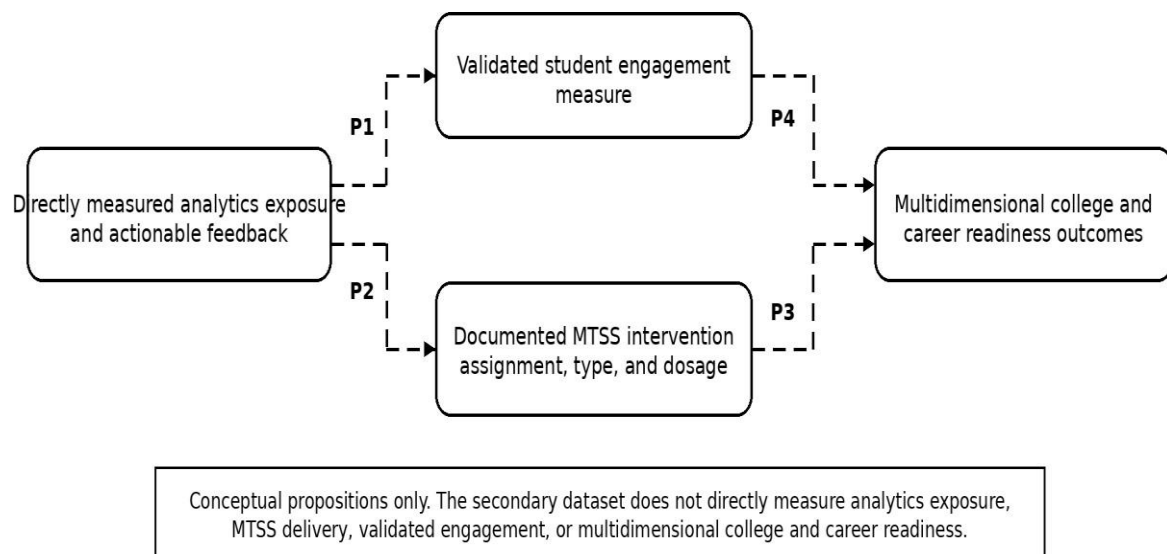


Figure 2. Conceptual propositions and direct measurement requirements for future institutional validation

6. Secondary-Data Measurement Adequacy Assessment

6.1 Analytic Purpose and Dataset

The empirical component was designed to examine measurement adequacy and sensitivity, not to test or validate the conceptual propositions. The Student Performance and Learning Behaviour Dataset contains 14,003 rows and 16 integer-coded variables related to study behaviour, participation, resources, technology use, and academic performance

(Najem et al., 2025). No values were missing. The file contains 1,534 exact repeated profiles. Without a unique student identifier, these profiles cannot be classified as repeated observations or as different students with the same coarse coded responses; their occurrence is also plausible because several variables have only two or three possible values. All records were retained in the primary analysis, and exclusion of repeated profiles was used as a sensitivity check ($n = 12,469$).

Table 3. Proxy construction, alternative weighting, and measurement status

Summary	Indicators and bounds	Primary and alternative construction	Measurement status
DLA	StudyHours (1710-02); OnlineCourses (1710-02); EduTech (0/1)	Primary: equal mean after 1710-02 scaling. Alternative: .45, .35, .20.	Digital activity summary; not verified analytics exposure or feedback.
API	Resources (1710-02); Attendance (1710-02); AssignmentCompletion (1710-02)	Primary: equal mean. Alternative: .20, .40, .40.	Academic participation summary; not support received or MTSS delivery.
ERI	Discussions (0/1); Extracurricular (0/1); Motivation (1710-02)	Primary: equal mean. Alternative: .35, .20, .45.	Engagement-related indicators; not a validated engagement scale.
ASP	ExamScore (1710-02)	Rescale ExamScore to 1710-02.	Academic score only; not multidimensional CCR.
Sensitivity outcome	FinalGrade (1710-02)	Reverse order for ordinal-logistic check.	Categorical examination outcome; not combined with ExamScore.

6.2 Proxy Construction and Index Specification

All the selected indicators were converted to a common 1–5 scale using min–max normalization to make them comparable. The recalibrated value was determined as

Scaled value = $1 + 4 \times [(Original\ value - Minimum\ value) / (Maximum\ value - Minimum\ value)]$

Using the formula given in equation (1), we shall be scaling the value of each attribute.

In this article, the Original value refers to the value of the indicator as observed. The Minimum value and Maximum value refers to the lower and upper limits of the coding scale. To obtain values ranging between 1 and 5 these normalized values are multiplied by 4 and then add 1. Thus, 1 will represent the lowest value and 5 the highest value and other observations will be proportionately placed between both limits.

The construction of three proxy formative indices that is Digital Learning Activity (DLA), Academic Participation (API), and the Engagement-Related Indicator (ERI) was done. In the main analysis, all component indicators were treated equally. In the DLA, study hours, online course participation, and educational technology use are combined. Blended Learning Resource Use, Attendance, and Assignment Completion Assessment. ERI incorporated involvement in debates, extracurricular and motivation. The academic performance of students is given a numeric proxy by the Academic Score Proxy (ASP). The selected indices were used as an analytical summary of selected indicators. They should not be interpreted as validated psychometric scales nor as a direct measure of analytics exposure, institutional support or student engagement. To a sensitivity analysis, another

6.3 Construct-Validity and Robustness Procedures

Standardised indicators were used in a principal component analysis as a dimensionality diagnostic only. For DLA, the first component accounted for 34.0% of the variance, with mixed-sign loadings; for API, the first component accounted for 33.8% of the variance, with mixed-sign loadings; and for ERI, the first component accounted for 34.2% of the variance, with mixed-sign loadings. The indicator sets were thus not found to be unidimensional latent scales, and therefore were not treated as such. For both the equal-weight and alternative-weight specifications, descriptive statistics, Pearson and

weighting scheme was also examined to see if the findings differed with different importance levels assigned to component indicators. The following illustrates how the alternative indices were calculated. $DLA = (0.45 \times Study\ Hours) + (0.35 \times Online\ Course\ Participation) + (0.20 \times Educational\ Technology\ Use)$ -- (2)

$API = (0.20 \times Learning\ Resource\ Use) + (0.40 \times Attendance) + (0.40 \times Assignment\ Completion)$ equation -- (3)

$ERI = (0.35 \times Participation\ in\ Discussions) + (0.20 \times Extracurricular\ Activities) + (0.45 \times Motivation)$ - (4)

DLA represents the student's learning-centric attitude which promotes learning in educational institutions.

The formula mentioned in (3) assigns weights to learning resource use, attendance, and assignment completion in the calculation of API.

The equation given as (4) in the context is $ERI = 0.35 \times Participation\ in\ Discussions + 0.20 \times Extracurricular\ Activities + 0.45 \times Motivation$.

The alternative DLA specification takes Study Hours to contribute 45%, Online Course Participation 35% and Educational Technology Use 20% to the index, for example. In much the same fashion, the assigned weights in the other indices sum to 100%.

The alternative weights were introduced for an analytical sensitivity check only and do not represent empirically validated measurement weights. The alternative specification was constructed to verify if the meaningful findings hold when one does not adhere to the equal-weighting assumption.

Spearman correlation and three HC3-robust ordinary least squares association models were reported. Standardised coefficients, 95% confidence intervals, model fit and variance inflation factors were computed. Further checks included were exact repeated profiles, which were modelled as ordinals, Final Grade. The analyses were repeated with pandas v2.2.3, SciPy v1.17.0, scikit-learn and statsmodels v0.14.6 in Python v3.13.5. The associations that are reported in the results of this dataset are not intended to inform decisions about the conceptual propositions as there is no direct measure of analytics exposure,

MTSS delivery, validated engagement, employability competence, internship performance, job placement, or career transition.

6.4 Ethics and Data Availability

The study did not require any direct recruitment or contact with participants, nor was any primary data created, but rather relied on an openly available, anonymised secondary data set. The data set can be found at Zenodo (Najem et al., 2025). Analysis scripts and outputs are provided in a format that can be reproduced. If authors are requested to submit a determination of the ethical aspects of the research article to the journal/institution, they should report the determination made.

7. Implementation Model for Digital Higher Education

The coordinated institutional infrastructure, faculty practice, student-support services, and governance are needed to implement the learning analytics-based MTSS framework. Data is generated in digital learning environments by the use of LMS, online assessments, discussion tools, attendance systems, and career-development platforms. These data are only educationally useful when they are acted upon in a clear process that links indicators with professional review, tier placement, delivery of intervention, and progress monitoring. The implementation model thus takes place at institutional, faculty and student-support levels and is closed in a monitoring-evaluation-adjustment cycle.

7.1 Institutional Integration and Governance

Institutional level, the LMS and related platforms should provide approved data elements to a secure analytics environment. Each indicator needs to be defined in terms of purpose, retention time, access rights, consent and notification processes, and processes for correcting inaccurate data for each indicator. Dashboards should show understandable trends and not confusing risk labels, and should differentiate between automated alerts and confirmed support decisions. A cross-functional implementation team made up of academic leaders, learning-analytics experts, faculty,

advisors, career-services staff, information-technology staff, and data-protection staff should be in charge of calibration, equity review, and resource allocation. There is also a need to train faculty and advisors on how to interpret the dashboard, document interventions, and how to use student data responsibly.

7.2 Faculty-Driven Data-Informed Teaching

Faculty members convert analytics indicators to instructional action. Tier 1 practices are universal, such as course organisation, learning resources that are accessible, formative assessment, regular feedback, guidance on digital literacy and career-awareness activities for all students. At cohort level information is analysed on the dashboard and used to identify common barriers and to design courses to address these. Students with moderate learning difficulties are provided with targeted academic support at Tier 2, such as individualised instruction, structured support, small group tutorials, mentoring, study-planning support and focused skill-development activities. Faculty record selected intervention, length of intervention, evidence to be used to measure progress.

Tier 3 offers intensive and individualised support for students with severe, persistent and/or support that is not effective when provided at Tier 2. A coordinated support plan is created by faculty and academic advisors, counsellors, accessibility services and career professionals. The plan will consist of one-to-one tutoring, individualised assessment arrangements, counselling or well-being referrals, intensive academic planning, structured employability coaching and regular progress reviews, depending on the student's situation. The transition to Tier 3 should not be made based solely on an automated score; it must be reviewed by a professional, supported by contextual evidence and provide an opportunity for the student to be involved in the decision about support.

Faculty judgment and student communication are always key at each level. Use of analytics should be used to start inquiry and support, not

to label. Records and outcomes from interventions should be returned to the analytics environment to assess if the intervention(s) were timely, appropriate and effective.

7.3 Student-Centred Career Development

The student-support element expands the scope beyond academic achievement to CCR development. Career analytics dashboards can provide a snapshot of progress toward course outcomes, projects, internships, digital competencies, communication, teamwork, and other indicators of readiness defined by the institution. Students should be able to access and share their own information, identify their areas for development and access appropriate mentoring, internships, workshops, or career guidance. When implementing the framework at the institutional level, direct and validated measures of career-readiness should be included in the secondary data used for the measurement demonstration, as there are limited participation indicators and examination performance in this secondary dataset.

7.4 Analytics-Driven Intervention Workflow

There are five stages in the operational workflow which are connected to each other. First, the approved data are gathered from the LMS, assessment systems, attendance records and student-support platforms. Second, it validates and normalizes the data, generates meaningful metrics and presents trends on role-specific dashboards. Third, a trigger that is based on a rule initiates a faculty or advisor review. Illustrative Tier 2 triggers can be two or more of the following indicators within two weeks: less than three meaningful LMS sessions per week;

assignment completion of less than 60%; attendance of less than 70%; assessed performance drops by 10 percentage points or more; and seven or more consecutive days of inactivity. These are examples of values and are not necessarily the cutoffs and should be adjusted to the local course design and student population.

Fourth, the reviewer confirms the context and selects an intervention. Tier 1 remains the default universal provision; Tier 2 is considered when moderate risk indicators are confirmed; and Tier 3 review is considered when assignment completion falls below 40%, attendance falls below 50%, a locally validated high-risk probability exceeds .70, or the student shows insufficient improvement after two to four weeks of Tier 2 support. No automatic escalation should occur without professional review. Fifth, engagement, performance, and support uptake are reassessed at a defined interval. Improvement may lead to reduced support, limited improvement may lead to adjustment or escalation, and all outcomes are fed back into the system for evaluation and threshold recalibration.

The feedback loop closes the implementation cycle: data collection -> analytics processing -> dashboard alert -> professional review -> tiered intervention -> progress monitoring -> re-evaluation. Institutions should routinely audit false-positive and false-negative alerts, differential impacts across student groups, response time, intervention completion, and student feedback. This process enables continuous improvement while reducing the risk that analytics functions as surveillance rather than support.

Table 4. Implementation roadmap for learning analytics-driven MTSS

Phase and timeline	Key activities	Lead responsibility	Measurable implementation outcome
1. Governance and readiness Months 1710-02	Define purposes, approved indicators, privacy controls, escalation rules, and equity review.	Academic leadership; data governance; ethics/privacy team	Approved governance protocol; every indicator documented with an owner and purpose.
2. Data integration Months 1710-02	Connect and validate LMS, assessment, attendance, and	IT; analytics team; LMS administrators	Target at least 95% data completeness; resolve

	support-service data feeds; configure dashboards.		validation errors before the pilot.
3. Faculty preparation and pilot Months 1710-02	Train reviewers; pilot dashboards and intervention documentation in selected courses.	Faculty development; programme leaders; advisors	Target at least 80% reviewer training completion; monitor alert-review time.
4. Tiered intervention delivery Months 1710-02 / one semester	Apply locally calibrated triggers; deliver Tier 1, Tier 2, and Tier 3 supports; document uptake and response time.	Faculty; advisors; counselling; career services	Target documented review for at least 90% of confirmed alerts; report support uptake and response time.
5. Evaluation and scaling End of pilot and each semester	Assess engagement, academic progress, intervention completion, student feedback, and group-level fairness; recalibrate thresholds.	Institutional research; quality assurance; implementation team	Complete an outcome and equity report; review false alerts and document the scale-up decision.

Note. The roadmap is indicative rather than prescriptive. Timelines, thresholds, and targets must be calibrated to local infrastructure, course design, student characteristics, staffing capacity, and ethical-review requirements.

8. Results of the Measurement Adequacy Assessment

This section illustrates the possibilities and limitations of inferences that can be drawn when convenient secondary variables are mapped to a conceptually richer framework. All 14,003 records were kept in the primary analysis and four neutral summaries (digital learning activity [DLA], academic participation [API], an engagement-related indicator index [ERI], and an academic score proxy [ASP]). No direct measures of analytics exposure, MTSS intervention delivery, validated engagement or multidimensional CCR. The results are thus a description of the behaviour of the proxy

construction, and not a test of the conceptual propositions.

8.1 Descriptive Profile

The equal-weight 1-to-5 summaries are summarised in Table 5. Mean values were near the scale midpoint: DLA $M = 3.12$, API $M = 3.06$, ERI $M = 3.20$, and ASP $M = 3.02$. These values represent the public file as a result of the transformation and should not be considered as institutional norms or validated construct scores.

Figure 3 visually summarizes the central tendency and spread of the four equal-weight proxy summaries reported in Table 5.

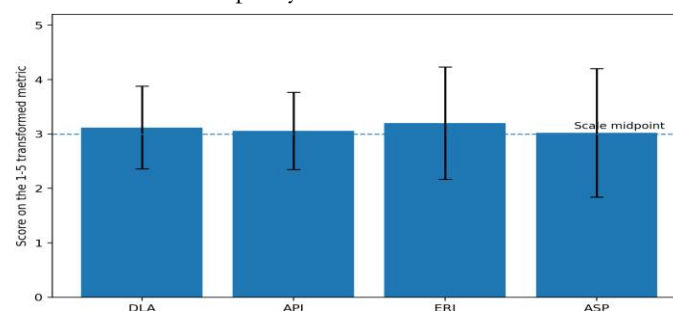


Figure 3. Descriptive profile of the equal-weight proxy summaries (means with standard deviations)

Table 5. Descriptive statistics for the equal-weight proxy summaries

Variable	N	Mean	SD	Minimum	Maximum
Digital learning activity (DLA)	14,003	3.12	0.76	1.07	4.83

Academic participation (API)	14,003	3.06	0.71	1.00	4.97
Engagement-related indicators (ERI)	14,003	3.20	1.03	1.00	5.00
Academic score proxy (ASP)	14,003	3.02	1.18	1.00	5.00

8.2 Correlation Analysis

Pearson correlations are presented in Table 6. Coefficients ranged from -.026 to .024. DLA was not related to API ($r = .012$, $p = .141$) or ERI ($r = .005$, $p = .526$). API was not related to ASP ($r = .008$, $p = .348$). ERI had a statistically significant but practically negligible negative relationship with ASP ($r = -.026$, $p = .002$), and DLA had a negligible direct correlation with ASP ($r = .024$, $p = .005$). Spearman coefficients produced the same substantive pattern.

Figure 4 complements Table 6 by displaying the near-zero correlation structure among the four proxy summaries.

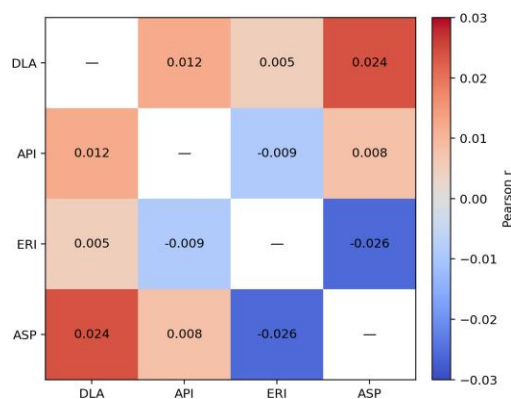


Figure 4. Off-diagonal Pearson correlations among DLA, API, ERI, and ASP

Table 6. Pearson correlation matrix

Variable	DLA	API	ERI	ASP
DLA	1			
API	.012	1		
ERI	.005	-.009	1	
ASP	.024**	.008	-.026**	1

Note. ** $p < .01$. All off-diagonal coefficients are negligible in magnitude.

8.3 Association and Weighting-Sensitivity Analysis

HC3-robust ordinary least squares models were estimated as descriptive association checks. Table 7 shows model fit for the main equal-weight summaries, and Table 8 shows a comparison of the standardised coefficients for equal-weight

and alternative domain-priority constructions. These models do not test the conceptual propositions since the variables are not construct aligned measures. The equal-weight association estimates with 95% confidence intervals are presented in Figure 5 and the alternative weighting does not substantially alter the substantive interpretation in Figure 6.

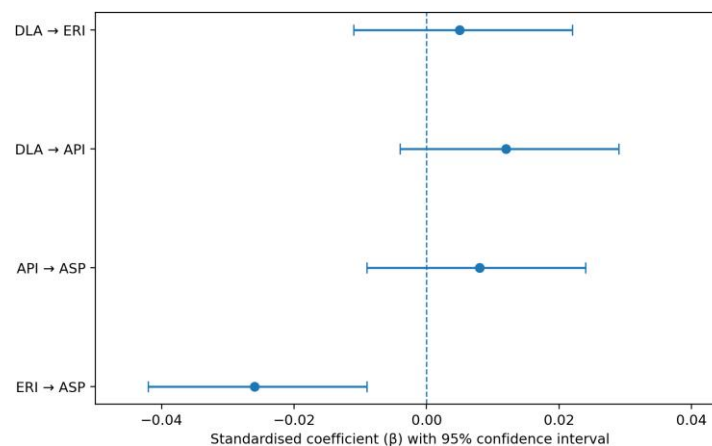


Figure 5. Equal-weight standardised association estimates with 95% confidence intervals

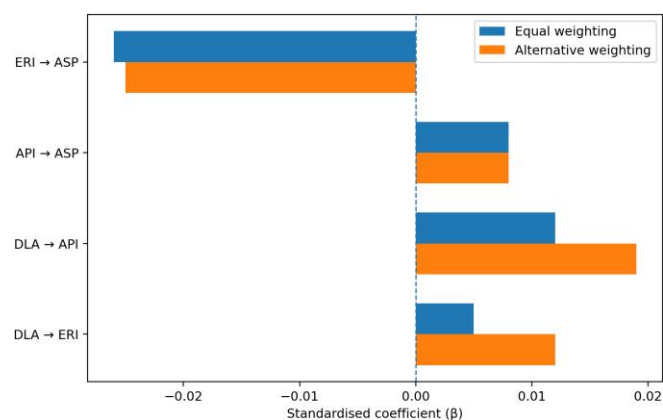


Figure 6. Comparison of equal-weight and alternative-weight standardised coefficients

Table 7. Primary equal-weight association model fit

Model	Outcome	Predictors	N	R ²	Adjusted R ²	F test
M1	ERI	DLA	14,003	< .001	< .001	F(1, 14,001) = 0.40, p = .526
M2	API	DLA	14,003	< .001	< .001	F(1, 14,001) = 2.16, p = .141
M3	ASP	API, ERI	14,003	.001	.001	F(2, 14,000) = 5.09, p = .006

Table 8. Association estimates under equal-weight and alternative-weight constructions

Exploratory association	Equal β	p	95% CI	Alternative β	p	95% CI	Interpretation
DLA -> ERI	.005	.521	[-.011, .022]	.012	.135	[-.004, .029]	Negligible under both constructions.
DLA -> API	.012	.143	[-.004, .029]	.019	.026	[.002, .036]	Significant only under alternative weighting; R ² =.00036 and practically null.
API -> ASP	.008	.360	[-.009, .024]	.008	.330	[-.008, .025]	Negligible under both constructions.

ERI -> ASP	-.026	.002	[-.042, .009]	-	-.025	.003	[-.042, .009]	-	Negligible negative association; not interpretable as an SDT test.
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The equal weight models accounted for .003% to .073% of the variance in the outcome. The substantive conclusion did not change when using alternative weighting. The alternative specification had a coefficient of .026 for the DLA-API, but only a standardised effect of .019 and an R^2 of .00036, which is not practically meaningful and does not represent support delivery. Both specifications (ERI-ASP = -.026 and -.025) yielded small negative coefficients. The substantive pattern was also the same when repeated profiles were excluded and FinalGrade was used in an ordinal model. Therefore, the near-zero relationships are not sensitive to the scoring options tested and the PCA diagnostic reveals that the indicator sets are not coherent latent constructs.

8.4 Construct-Validity Findings

Figure 7 adds a visual summary of the principal-component diagnostic, highlighting that none of the indicator groupings behaves as a strong one-factor scale.

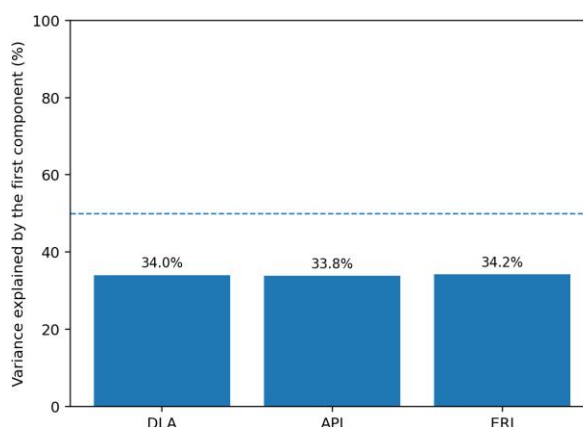


Figure 7. Variance explained by the first principal component for each indicator grouping

The principal empirical finding is a measurement finding. MTSS cannot be operationalized in the dataset as there is no information provided about tier assignment, type of intervention, dosage, fidelity of implementation, and response to support. It cannot operationalise CCR as it only measures a limited academic outcome in the form of examination score. It also lacks a robust test of the Self-Determination Theory, as the ERI is composed of participation in discussion and extracurricular activities, as well as one motivation code, but does not include a validated multi-item measure of autonomy, competence, relatedness and engagement. The small negative correlation between ERI-ASP should not, therefore, be seen as evidence against SDT. On the contrary, it shows how the theoretically significant relationship can vanish or even be inverted, when constructs are proxied by weak and heterogeneous proxies.

Table 9. Principal component dimensionality diagnostic

Indicator summary	PC1 variance	PC1 loadings	Diagnostic interpretation
DLA	34.0%	StudyHours .586; OnlineCourses -.482; EduTech .651	Mixed signs; no coherent one-factor scale.

API	33.8%	Resources -.632; Attendance .665; AssignmentCompletion .397	Mixed signs; no coherent one-factor scale.
ERI	34.2%	Discussions -.611; Extracurricular .391; Motivation .689	Mixed signs; no coherent one-factor scale.

9. Discussion

9.1 Theoretical and Methodological Contribution

The paper's key contribution is the four domains that are integrated into an analytics-to-action architecture. Learning analytics provides evidence, MTSS provides structure to the response, SDT provides the motivational conditions for the effectiveness of the response, and CCR provides the multidimensional outcome space. This measurement demonstration complements this synthesis by demonstrating how the proposed paths can't be tested without behavioural proxies that do not include exposure, intervention, validated engagement, and readiness constructs. The near zero coefficients thus set a measurement limit instead of an effectiveness judgement.

9.2 Implications for Practice and Policy

The framework aims to ensure that students' learning is supported in a timely and consistent way by linking continuous learning indicators to structured decisions about interventions. Tier 1: Cohort-level analytics can provide information for universal improvements to course design, feedback, digital-literacy support, and career-awareness provision. Professionally confirmed indicators can be used to enhance outreach and differentiated assistance at Tier 2 and Tier 3. The benefits are contingent on data quality, thresholds which are locally appropriate, student engagement and the institution's ability to provide the recommended support.

The model also links identified need to an explicit level of support. Students with moderate difficulties can receive targeted academic and study-skills assistance, while students with persistent or complex needs can receive

coordinated individualised support. CCR development can be incorporated through mentoring and direct evidence from projects, internships, digital-literacy tasks, communication, teamwork, and problem-solving activities. These competencies must be measured directly when the framework is evaluated.

At institutional level, aggregated and appropriately anonymised information can support evaluation of student-support services, resource allocation, programme design, and equity. Analytics should function as one component of a socio-technical support system rather than as a stand-alone monitoring tool. Implementation should therefore include transparent governance, human oversight, student communication, intervention documentation, and routine audits of false alerts and differential impacts.

9.3 Limitations and Future Empirical Validation

The study has four principal limitations. First, the conceptual framework was developed through a purposeful theory-synthesis rather than a systematic review. Second, the secondary dataset contains coarse integer-coded variables and no direct measures of intervention exposure or CCR. Third, the formative index weights, although examined through sensitivity analysis, are not validated measurement weights. Fourth, the framework has not yet undergone stakeholder co-design, expert validation, feasibility testing, or institutional outcome evaluation.

The secondary-data demonstration neither validates nor falsifies the proposed framework. A prospective pilot should record analytics exposure and feedback, professional review decisions, tier assignment, intervention type and

dosage, implementation fidelity, support uptake, repeated progress measures, and student-reported experience. Engagement should be assessed with a validated instrument aligned with self-determination theory, while CCR should include academic preparedness, employability competencies, project and internship performance, digital literacy, career self-management, placement, and transition outcomes. The propositions in Figure 2 can then be evaluated longitudinally using preregistered multilevel models, mediation analysis where theoretically justified, and equity audits. This pilot constitutes a distinct second study because it will evaluate implementation and outcomes rather than repeat the present conceptual and measurement contribution. The framework should be structurally reviewed by experts, based on content-validity criteria, before implementation at student level, and should be agreed upon on the level of the tier and the type of intervention. This was an intermediate step that would evaluate theoretical coherence, operational clarity, feasibility and ethical acceptability, but not replace the step of outcome validation.

10. Conclusion

Digital learning environments open opportunities for institutions to recognise the needs that are emerging and provide timely and

differentiated support. This study created a framework that integrates learning analytics with evidence that is interpretable by teachers, MTSS with universal, targeted, and intensive interventions, and continuous monitoring with evidence for adjustment. The concept of self-determination theory helps to understand the role of autonomy-supportive feedback, competence development and meaningful relationships in enhancing engagement; and CCR outlines the intended multidimensional outcome domain. The secondary data set was not available for the constructs needed for validation: there were virtually no associations between the equal-weight and alternative weight analyses, and the dimensionality diagnostics were not coherent among the proxy indicators. The findings do not indicate that the proposed relationships are not effective, but rather they indicate that construct aligned measurement is a necessary condition for meaningful evaluation. The paper provides an operational framework of analytics-to-action, a critique of the measurement process in a clear manner, and a full data specification for a potential institutional pilot. The next step in the research process should involve testing the feasibility of implementation, fidelity of the intervention, engagement mechanisms, and multidimensional CCR outcomes with longitudinal institutional data.

References

- Caspari-Sadeghi, S. (2023). Learning assessment in the age of big data: Learning analytics in higher education. *Cogent Education*, 10(1), Article 2162697. <https://doi.org/10.1080/2331186X.2022.2162697>
- Chiu, T. K. F. (2022). Applying the self-determination theory to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education*, 54(S1), S14-S30. <https://doi.org/10.1080/15391523.2021.1891998>
- Conley, D. T. (2014). New conceptions of college and career readiness: A profile approach to admission. *Journal of College Admission*, 223, 1710-02.
- Deci, E. L., & Ryan, R. M. (2000). The 'what' and 'why' of goal pursuits: Human needs and the self-determination of behaviour. *Psychological Inquiry*, 11(4), 1710-02. https://doi.org/10.1207/S15327965PLI1104_01
- D'Souza, M., Kumar, P. R., & Fernandes, S. (2020). Effective inclusion of multitier support system framework for college and career readiness. *International Journal of Indian Psychology*, 8(4), 1710-02. <https://doi.org/10.25215/0804.178>
- Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(1710-02), 1710-02. <https://doi.org/10.1504/IJTEL.2012.051816>
- Fuchs, D., & Fuchs, L. S. (2006). Introduction to response to intervention: What, why, and how valid is it? *Reading Research Quarterly*, 41(1), 1710-02. <https://doi.org/10.1598/RRQ.41.1.4>

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- Gašević, D., Tsai, Y.-S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *International Journal of Information and Learning Technology*, 36(4), 1710-02. <https://doi.org/10.1108/IJILT-1710-02-0024>
- Hernández-de-Menéndez, M., Morales-Menendez, R., Escobar, C. A., & Ramírez-Mendoza, R. A. (2022). Learning analytics: State of the art. *International Journal on Interactive Design and Manufacturing*, 16, 1710-02. <https://doi.org/10.1007/s11710-02-01710-02>
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
- Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, 68(4), 1710-02. <https://doi.org/10.1007/s11710-02-09788-z>
- Jaakkola, E. (2020). Designing conceptual articles: Four approaches. *AMS Review*, 10(1710-02), 1710-02. <https://doi.org/10.1007/s11710-02-01710-02>
- McIntosh, K., & Goodman, S. (2016). *Integrated multi-tiered systems of support: Blending RTI and PBIS*. Guilford Press.
- Morningstar, M. E., Lombardi, A., Fowler, C. H., & Test, D. W. (2017). A college and career readiness framework for secondary students with disabilities. *Career Development and Transition for Exceptional Individuals*, 40(2), 1710-02. <https://doi.org/10.1177/2165143415589926>
- Najem, K., Ziti, S., & Zaoui Seghroucheni, Y. (2025). *Student performance and learning behavior dataset for educational analytics* [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.16459132>
- Raković, M., Gašević, D., Hassan, S. U., Ruipérez-Valiente, J. A., Aljohani, N., & Milligan, S. (2023). Learning analytics and assessment: Emerging research trends, promises and future opportunities. *British Journal of Educational Technology*, 54(1), 1710-02. <https://doi.org/10.1111/bjet.13301>
- Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, 61, Article 101860. <https://doi.org/10.1016/j.cedpsych.2020.101860>
- Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, 57(10), 1710-02. <https://doi.org/10.1177/0002764213498851>
- Siemens, G., & Baker, R. S. J. d. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 1710-02). Association for Computing Machinery. <https://doi.org/10.1145/2330601.2330661>
- Srivastava, N., Nawaz, S., Tsai, Y.-S., & Gašević, D. (2024). Curriculum analytics of course choices: Links with academic performance. *Journal of Learning Analytics*, 11(1), 1710-02. <https://doi.org/10.18608/jla.2024.8095>
- Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, 89, 1710-02. <https://doi.org/10.1016/j.chb.2018.07.027>
- Williamson, B. (2016). Digital education governance: Data visualization, predictive analytics, and 'real-time' policy instruments. *Journal of Education Policy*, 31(2), 1710-02. <https://doi.org/10.1080/02680939.2015.1035758>
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