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ARTICLE

SUSTAINABLE COMPETITIVE INTELLIGENCE FOR ACADEMIC CAPABILITY DEVELOPMENT: A VALIDATION-READY GOVERNANCE, SENSING AND FORESIGHT FRAMEWORK

INTELIGÊNCIA COMPETITIVA SUSTENTÁVEL PARA O DESENVOLVIMENTO DE CAPACIDADES ACADÊMICAS: UM FRAMEWORK DE GOVERNANÇA, MONITORAMENTO E PROSPECTIVA PREPARADO PARA VALIDAÇÃO

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ABSTRACT

Purpose: The purpose of this study is to create a Sustainable Competitive Intelligence (SCI) framework for academic capability development, which explains how the faculty competence evidence can be translated into the input of the intelligence cycle, namely sensing, analysis, dissemination, governance and use in decision-making.

Methodology/approach: The study is based on a secondary study design that is validation-ready. Rather than serving as a direct measure of CI adoption, a public Figshare faculty competence dataset is used as evidence input. The analysis establishes the competence domains of the intelligence cycle, formulates a clear prioritisation logic and describes specific organisational validation measures those future institutions have to implement via expert review, Delphi/AHP weighting and KPI tracking.

Originality/Relevance: The article looks at educational analytics with a new perspective, as CI is introduced as an organizational ability instead of a dashboard or a descriptive data exercise.

Key findings: The framework demonstrates that competence evidence can be used to contribute to intelligence products like capability-gap briefs, segmentation notes, risk signals, development-priority maps and governance dashboards. The proposed indicators of digital competence are not considered as an empirical measure of CI, but rather as one source of intelligence.

Theoretical/methodological contributions: Provides a CI-SHRM-KM-TR framework and a logic that can be validated (CPI) without empirical data from organizations in the future, and the boundaries of claims are just explicit.

Keywords: Competitive Intelligence. Sustainable Competitive Intelligence. Intelligence Cycle. Environmental Scanning. Strategic Foresight. Academic Capability. Knowledge Management

RESUMO

Objetivo: O objetivo deste estudo é desenvolver um framework de Inteligência Competitiva Sustentável (Sustainable Competitive Intelligence – SCI) para o desenvolvimento de capacidades acadêmicas, explicando como evidências de competências docentes podem ser convertidas em insumos para o ciclo de inteligência, incluindo monitoramento (*sensing*), análise, disseminação, governança e utilização na tomada de decisão.

Metodologia/abordagem: O estudo adota um desenho de pesquisa secundário preparado para validação (*validation-ready*). Em vez de servir como uma medida direta da adoção da Inteligência Competitiva, utiliza um conjunto de dados público do Figshare sobre competências docentes como fonte de evidências. A análise identifica os domínios de competências associados ao ciclo de inteligência, estabelece uma lógica clara de priorização e descreve medidas específicas de validação organizacional que futuras instituições deverão implementar por meio de avaliação de especialistas, ponderação via Delphi/AHP e monitoramento de indicadores-chave de desempenho (KPIs).

Originalidade/Relevância: O artigo propõe uma nova perspectiva para a análise educacional ao posicionar a Inteligência Competitiva como uma capacidade organizacional estratégica, em vez de tratá-la apenas como um painel de indicadores ou um exercício descritivo de análise de dados.

Principais resultados: O framework demonstra que evidências de competências podem ser utilizadas para produzir produtos de inteligência, como relatórios sobre lacunas de capacidades, notas de segmentação, sinais de risco, mapas de prioridades para desenvolvimento e painéis de governança. Os indicadores propostos de competências digitais não são considerados uma medida empírica de Inteligência Competitiva, mas sim uma das fontes de informação que alimentam o processo de inteligência.

Contribuições teóricas/metodológicas: O estudo propõe um framework integrando Inteligência Competitiva (CI), Gestão Estratégica de Recursos Humanos (SHRM), Gestão do Conhecimento (KM) e Recursos Tecnológicos (TR), bem como uma lógica de validação (CPI) passível de aplicação futura em organizações, mesmo sem dados empíricos imediatos. Além disso, explicita claramente os limites das inferências e das conclusões propostas.

Palavras-chave: Inteligência Competitiva. Inteligência Competitiva Sustentável. Ciclo de Inteligência. Monitoramento Ambiental. Prospectiva Estratégica. Capacidades Acadêmicas. Gestão do Conhecimento.

1. INTRODUCTION

Universities function in a technological context, a policy-driven one, a context of labour market uncertainty, and a context of rising expectations for outcomes-based competence training. The central question this study seeks to answer is not whether faculty members have digital competences or not, but how the integration of the distributed evidence of faculty competences can be made into sustainable, competitive information for strategic decisions. The difference is significant because data alone cannot be intelligence until they are linked to a specific decision problem, understood through an organizational process and shared with actors who are able to act upon it. Digital capability, governance, culture and process alignment are also identified as key prerequisites for digital transformation in higher education and digital organizational transformation (Gkrimpizi et al., 2023; Verhoef et al., 2021; Bongomin et al., 2020; Benavides et al., 2020). Academic Capability Development is more than just Educational Analytics, from a Sustainable Competitive Intelligence point of view. It needs competitive sensing, environmental scanning, intelligence networks, interpretation based on foresight, governance rules, dissemination channels and feedback loops. These components enable the competence evidence to become a dataset for diagnosis, but also to be integrated into a sustainable development and institutional intelligence architecture.

This study uses empirical input as a public faculty digital competence data set. The data set, however, is not regarded as an actual measure of CI adoption. It is utilized as an input to an intelligence process which can be done within a CI cycle. This positioning directly addresses the methodological boundary of the study, as the secondary competence evidence can inform the development of a framework, rather than providing proof of an institution's adoption of CI, sustainable competitive advantage and/or governance model validation. Thus, this study seeks to formulate a validation-ready academic capability development SC framework. It supports, by integrating the concepts of CI, strategic human resource management (SHRM), knowledge management and readiness of technology into a framework that transforms evidence into products of intelligence, decision pathway, future institutional KPIs. This positioning aligns with the recent findings that the business-intelligence capability and competitive-intelligence practices are correlated with performance and sustainable competitiveness and decision-oriented organizational capability (Ibrahim et al., 2025; Chen & Lin, 2021). The article is deliberately cautious: a structured secondary framework is provided, and a validation protocol is offered for the future, not a completed primary-data validation study.

2. THEORETICAL FRAMEWORKS

2.1 Competitive Intelligence, Environmental Scanning and Competitive Sensing

For the purpose of this study, Competitive Intelligence is considered as a competency of organisation to sense, interpret and disseminate strategically relevant information. Recent scholarship in competitive-intelligence and business-intelligence places emphasis on organisations' sensing of change in their environments, the interpretation of ‘weak signals' and the translation of evidence into intelligence that is relevant to organizational decision making, linking intelligence outputs to strategy formulation and decision making (Cavallo et al., 2021; de las Heras-Rosas & Herrera, 2021; Niu et al., 2021; Ranjan & Foropon, 2021). The university is not viewed as just a commercial competitor in this article, but as an organisation that needs to be sensitive to capability gaps, the requirements of policy, technological change and the expectations of stakeholders.

Competitive sensing is the capability of an institution to identify significant changes in time before they reach a level that is a problem with the operation. Sensing may refer to evidence of faculty competence, accreditation needs, student-support indicators, labour-market signals, as well as curriculum needs and digital transformation priorities in academic capability development. Strategic recruitment, institutional decision support and implementation of institutional strategies are recent higher education uses of CI that are still poorly organized and/or poorly understood (Maluleka & Chummun, 2023; Mgweba et al., 2024). Table 1 illustrates how the concepts of this study are operationalised, but does not imply that the public dataset is an exact measure of CI adoption.

Table 1. Operationalization of the Sustainable Competitive Intelligence Framework

Construct	Operational meaning in this study	Role in the article
Competitive intelligence	Organizational process for defining intelligence needs, sensing evidence, analyzing priorities, disseminating intelligence products and evaluating decision use.	Central theoretical construct and organizational capability.
Environmental scanning	Continuous monitoring of internal and external evidence such as capability gaps, policy pressures, technology change and stakeholder expectations.	Source of intelligence needs and early signals.
Strategic foresight	Forward-looking interpretation of signals to anticipate future capability requirements and development risks.	Links current evidence to future academic capability planning.
Strategic HRM	Translation of intelligence into training, mentoring, workload support, micro-credentials and career-development decisions.	Implementation pathway for intelligence use.
Knowledge management	Repositories, dashboards, communities of practice and reusable resources that retain and share intelligence.	Dissemination and organizational learning mechanism.
Technology readiness	Faculty and institutional capacity to adopt digital practices and benefit from development interventions.	Contextual condition shaping implementation.
Academic capability development	Improvement of faculty capability in digital pedagogy, assessment, resources, professional engagement and student support.	Outcome domain of CI-informed decision-making.

2.2 Intelligence Networks, Dynamic Capability and Strategic Foresight

Competitive intelligence is dependent on networks and not just individual analysts. A network of intelligence links academic affairs, HRM, digital learning units, libraries, quality assurance units, department heads and faculty-development centers. These actors are not just recipients of reports; they are also the ones who set the agenda for intelligence needs, make sense of evidence, review priorities, and give feedback following decision-making. Research on business-intelligence governance and the adoption of BI in higher education confirms that focus on organizational readiness, information culture, governance roles and decision structures (Combita Nino et al., 2020; Hmoud et al., 2023).

Dynamic intelligence capability is the ability of an organization to sense change and reconfigure development priorities and learn from outcomes over and over. For universities, it is important that capability evidence is not used and stored in the back of their minds. It should be fed into periodic cycles of intelligence, future-oriented thinking and institutional learning. This theoretical extension minimizes the reliance on educational analytics, therefore, placing the article more in line with the S.C.I topic, which focuses on supporting strategy formulation, and not just a reporting activity (Cavallo et al., 2021; de las Heras-Rosas & Herrera, 2021).

2.3 Intelligence Cycle, Governance and Dissemination

The framework is based on a formal intelligence cycle: direction, collection, processing, analysis, dissemination, decision use and evaluation. Direction is what the decision-makers need to know. Collection draws data from publicly available data sources, institutional surveys, labour-market information, accreditation requirements and strategic planning documents. These sources are prepared for comparison using the process of processing. Analysis converts evidence into intelligence products and dissemination makes the intelligence products available to responsible decision units.

This cycle is aligned with recent studies which reveal the value of big data analytics and organizational business intelligence is more in interpreting and decision making than being just an end product of a technical process (Niu et al.,2021; Ranjan & Foropon,2021). Governance establishes who decides on what intelligence is needed, who is interpreting evidence, who is receiving intelligence products, how the decisions are recorded and how the outcomes of the intelligence are reviewed. Dissemination should, in turn, not be an end to administration; it is a means of making intelligence useful. The intelligence-models logic used in this study is as shown in the figure below.

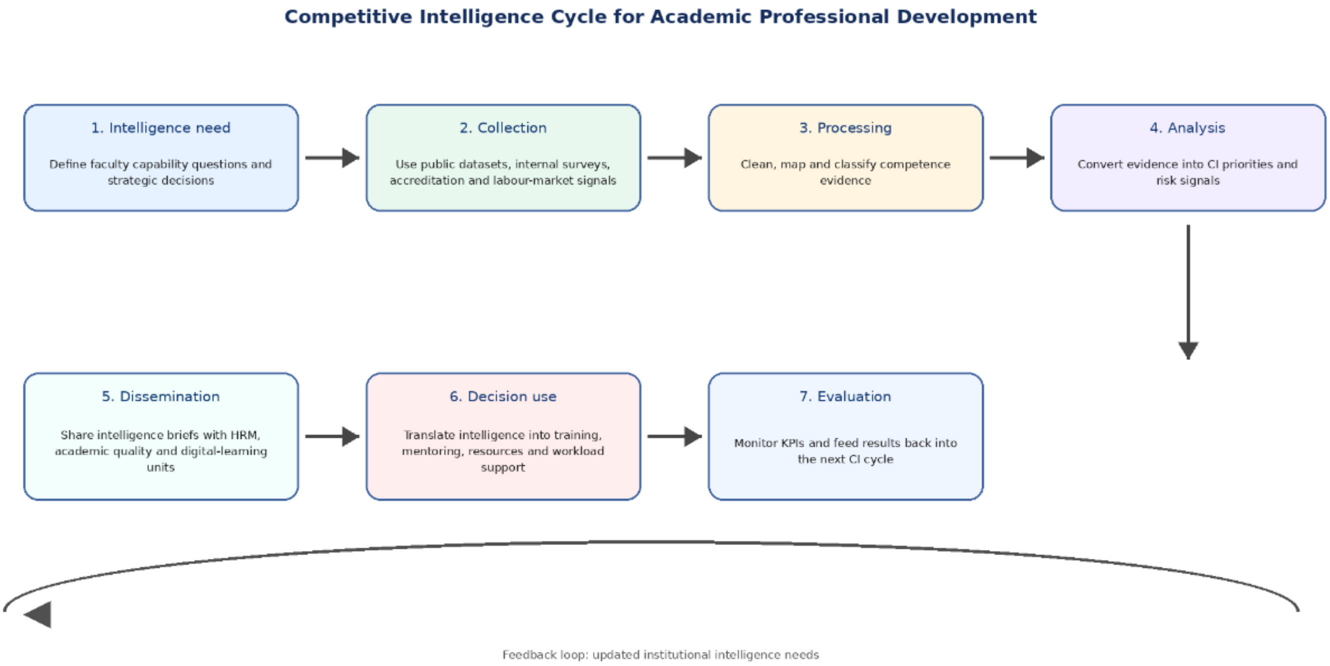

Figure 1. Competitive intelligence cycle for academic capability development

2.4 CI-SHRM-KM-TR Framework for Academic Capability Development

There are four mechanisms integrated in the CI-SHRM-KM-TR framework. CI is responsible for sensing and interpretation. Strategic HRM translates intelligence into development activities. Knowledge Management stores, shares and reuses Intelligence products. The feasibility of implementation is influenced by technology readiness. The framework does not state that public competence data is a direct measure of the CI adoption. In contrast, CI is translated into an organizational process that connects evidence and use of decisions. Table 1 operationalises the concept of CI, making it clear that this is not considered a general background concept. It is at the heart of the ability to link evidence, analysis, dissemination, decision-making and future evaluation. This separation is important because the study is based on secondary data and thus cannot rely on empirical confirmation.

3. METHODOLOGY

3.1 Research Design and Epistemological Positioning

The study uses a validation-ready secondary framework design. This design is appropriate because no primary interviews, surveys, case-study data or expert evaluations were collected. The purpose is not to prove that a university has adopted CI. The purpose is to construct a transparent SCI framework showing how faculty competence evidence could be processed through an intelligence cycle and later validated in a real organizational setting. This design directly addresses the methodological limitation identified by the reviewers. The article no longer presents the Delphi/AHP procedure or KPI assessment as completed validation. Instead, these elements are repositioned as future institutional validation requirements. Figure 2 summarizes the revised methodological workflow.

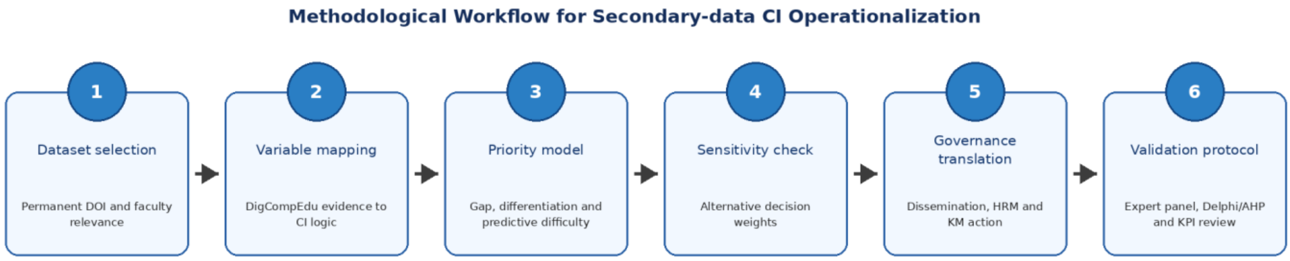

Figure 2. Methodological workflow for validation-ready secondary framework development

3.2 Dataset Source and Role as Intelligence Input

The empirical input is the Figshare dataset titled Data from the article titled Machine Learning Algorithms to Predict Digital Competencies in University Faculty (Moreira Choez et al., 2025b). The source article reports the use of the DigCompEdu Check-In instrument and 4,154 observations from faculty at the State University of Milagro and the Technical University of Manabi (Moreira-Choez et al., 2025a). The dataset was selected because it is public, traceable, recent and directly connected to faculty capability evidence. However, its role is limited. It is not a dataset about CI adoption, intelligence governance, strategic foresight or sustainable competitive advantage. It provides evidence that may enter the collection and processing stages of a CI cycle. Table 2 presents the dataset profile and clarifies its bounded role in the study.

Table 2. Dataset Profile and Bounded Role in the Study

Element	Description
Dataset title	Data from the article titled Machine Learning Algorithms to Predict Digital Competencies in University Faculty
Dataset DOI	https://doi.org/10.6084/m9.figshare.29036066.v1
Source publication	Moreira-Choez et al. (2025a), F1000Research, 14, Article 573
Population context	University faculty at the State University of Milagro and the Technical University of Manabi
Instrument	DigCompEdu Check-In questionnaire
Reported analytical file	4,154 observations used in the predictive phase
Role in this article	Evidence input for CI-cycle framework development; not a direct measure of CI adoption

3.3 Variable Mapping and CI Translation Logic

The dataset was not originally designed to measure CI, strategic HRM, knowledge management, technology readiness, intelligence networks or strategic foresight as latent constructs. Therefore, the study does not impose an artificial five-construct survey model on the data. Competence domains are treated as observable evidence of academic capability needs; socio-educational variables are treated as segmentation indicators; and predictive model results are treated as diagnostic signals. As shown in Table 3, the mapping translates dataset evidence into CI-cycle roles without claiming that the original data directly measure organizational intelligence capability. This protects the study from conceptual overclaiming and clarifies the boundary between evidence input and CI process.

Table 3. Mapping of Dataset Evidence to CI-Cycle Roles

Dataset evidence	CI-cycle role	Strategic interpretation
DigCompEdu competence areas	Evidence collection and processing	Competence domains identify possible capability gaps and development needs.
Academic level, age, gender and teaching experience	Segmentation and analysis	Faculty groups may require different development pathways and support levels.
Competence-level classification	Diagnostic intelligence	Classification difficulty indicates where richer contextual diagnosis may be needed.
Predictive model performance	Analytical signal	AUC and related metrics are decision-support signals, not automatic prescriptions.
Open dataset and documentation	Knowledge-management input	Reusable evidence supports transparency, auditability and future benchmarking.

3.4 Analytical Procedure

The analysis started with the identification of data sets and verification of their sources. Study source and dataset documentation were used to validate the instrument, population context, ethical statement, sample size and data availability. Competence areas were organised in a logical way, following the DigCompEdu logic, and understood as domains of competence evidence and not as actual indicators of actual CI adoption. It is based on the source article and the underlying open dataset (Moreira-Choez et al., 2025a; Moreira Choez et al., 2025b) which identified the faculty digital-competence context and the underlying open dataset.

Item-level chi-square evidence from the source was combined to create domain-level priority signals. The indicators provided by predictive models were read as diagnostic indicators. The higher the AUC value, the more competent levels are separable from the evidence that already exists, and the lower or more fluctuating the AUC values the more depth the diagnosis requires for competence, or more depth the consultation or the qualitative follow-up requires. The analytical process and quality controls are summarized in Table 4.

Table 4. Analytical Procedures and Quality-Control Measures

Stage	Procedure	Quality control
Dataset identification	Select a public dataset with DOI and faculty-level relevance.	Only a permanent DOI-based source was retained.
Context verification	Check source article for instrument, sample context, ethics and availability.	Source documentation was used instead of unverified assumptions.
Variable mapping	Map competence evidence to CI-cycle stages and strategic interpretation.	Avoid direct measurement claims for constructs absent from the dataset.
Evidence interpretation	Use competence priorities and predictive signals as intelligence inputs.	Report associations, priorities and decision signals, not causal effects.
Strategy translation	Develop governance, dissemination and future validation framework.	Link each recommendation to CI-cycle use and decision context.
Reproducibility	Report dataset DOI and source publication.	Allow reviewers to access the empirical input.

3.5 Mathematical Formulation and Sensitivity Logic

To make prioritization transparent, the study specifies a decision-support formulation rather than a causal statistical model. Let x_ij denote the standardized response of faculty member I on item j, and let D_k denote the set of items belonging to competence domain k. The model is used only to rank evidence-based

priorities for future decision support.
Equation (1): S_ik = (1 / n_k) * SUM(x_ij), for all j in D_k
Equation (2): G_k = max_g(MeanS_gk) – min_g(MeanS_gk)
Equation (3): PD_k = 1 – AUC_k
Equation (4): CPI_k = w1Z(G_k) + w2Z(ChiSq_k) + w3Z(PD_k), where w1 + w2 + w3 = 1
Equation (5): DAP_k = CPI_k * (1 + lambda1SHRM + lambda2KM + lambda3TR)

The weights in Equation (4) are not presented as expert-validated coefficients. They are adjustable decision parameters that require institutional validation through expert review, Delphi, AHP or sensitivity testing. Table 5 presents the weighting logic for future use.

Table 5. Weighting Logic for CPI Sensitivity and Future Institutional Validation

Scenario	Weighting logic	Purpose
Equal-weight scenario	w1 = .33, w2 = .33, w3 = .34	Tests whether priorities remain stable when all evidence components are treated similarly.
Gap-dominant scenario	w1 = .50, w2 = .25, w3 = .25	Gives more importance to subgroup competence gaps for equity-sensitive planning.
Differentiation-dominant scenario	w1 = .25, w2 = .50, w3 = .25	Prioritizes domains with stronger observed differences across academic levels.
Predictive-difficulty scenario	w1 = .25, w2 = .25, w3 = .50	Prioritizes domains that require richer diagnostic attention because competence levels are harder to classify.
Required future validation	Delphi, AHP or expert-panel weighting	Produces institution-specific weights before operational use.

3.6 Validation-Ready Protocol and Boundary of Primary Evidence

In this study, there was no attempt to do a primary validation of the organizations. No interviews, original surveys, case studies or expert evaluations were obtained. Thus, the framework is not proposed as an empirically proven one in a real university. The key to the revised methodology and renders an organisation "unvalidated".

Instead, the article prescribes a protocol that is ready for validation for future application. The following four stages of validation should be followed by a university that wants to implement the framework: (1) expert validation by academic affairs, HRM, digital learning, quality assurance and knowledge-management representatives; (2) Delphi or AHP weighting of the components of the CPI; (3) managerial evaluation of the intelligence products (briefs, dashboards and priority maps); and (4) longitudinal KPI assessment after the pilot implementation. The proposed validation protocol is presented in Table 6. The results in the table do not constitute a report of completed validation results. It is a methodological blueprint for guiding future researchers and institutions to take the framework from secondary evidence to organizational empirical testing.

Table 6. Validation-Ready Protocol for Future Organizational Application

Validation stage	Evidence to be collected in future application	Purpose
Expert review	Ratings from university managers and CI/HRM/quality specialists.	Assess conceptual clarity, CI centrality and organizational relevance.
Delphi or AHP weighting	Consensus scores or pairwise comparisons for CPI components.	Replace adjustable weights with institution-specific validated weights.
Managerial evaluation	Decision-maker review of intelligence briefs, dashboards and priority maps.	Assess usefulness for strategic HRM and governance decisions.
Pilot implementation	Training records, mentoring uptake, repository use and department adoption.	Test feasibility of translating intelligence into action.
Longitudinal KPI assessment	Pre/post competence movement and capability indicators over time.	Evaluate whether CI-informed actions improve institutional capability.

3.7 Methodological Boundary Regarding SEM, CFA and Latent Constructs

PLS-SEM, CFA and SEM were not estimated in the study as they were not the latent constructs in the original data set; CI, SHRM, KM, technology readiness, intelligence networks and strategic foresight were not directly measured as latent constructs in the study. If the method of latent-variable modelling were applied to unmeasured constructs, it would entail methodological overclaiming. The article thus reports secondary evidence and translation-logic and validation-ready procedures, but not causal latent variable relationships.

3.8 Ethical Considerations

No new data of the living subject were gathered. The data analysed are an already anonymised dataset that is publicly available, with its source cited. No attempt is made to re-identify and no claim of ownership of the original data. Ethical responsibility is ensured in the transparent reporting of the source and restricting the scope of claims and avoiding fake validation results.

4. RESULTS and DISCUSSION

4.1 Dataset as One Input in a Sustainable Competitive Intelligence Architecture

The data set will be useful for capability sensing but not an empirical object of CI itself. The redrafted interpretation recognizes that this data set is to be considered a single component of a larger intelligence architecture that would also need to include internal organizational data, managerial judgment, policy indicators, labour-market information and post intervention KPIs. This shift brings less reliance on DigCompEdu and educational analytics but still considers that capability evidence in the form of structure is required in digital-learning institutions and digital-transformation contexts (Alenezi, 2023; Farias-Gaytan et al., 2023; Gkrimpizi et al., 2023). The value of the CI is in the process of translation of the evidence itself: the evidence is gathered, processed, analyzed, converted to an intelligence product, disseminated to decision units and evaluated after action. The key outcome of the study is this organizational process.

4.2 Intelligence Products Generated from Competence Evidence

Instead of presenting results only as competence scores, the revised manuscript identifies the intelligence products that a university could generate from the evidence. Table 7 shows these outputs and their decision users.

Table 7. Intelligence Products and Decision Users

Intelligence product	Evidence source	Decision user	Decision purpose
Capability-gap brief	Domain-level competence signals	Academic affairs and HRM	Select development priorities.
Segmentation note	Academic level, experience and demographic variables	Departments and faculty-development center	Design differentiated training pathways.
Risk signal	Low or unstable classification patterns	Quality assurance and digital-learning unit	Identify areas needing contextual follow-up.
Knowledge brief	Reusable resources and documentation	Library and KM units	Store and disseminate development resources.
Foresight note	Current gaps linked to future capability requirements	Strategic planning committee	Anticipate emerging academic capability needs.

4.3 Competence-Priority Signals for CI Planning

The competence-priority signals are retained in a reduced form because they explain the evidence input used for intelligence planning. Figure 3 and Table 8 indicate that digital pedagogy, digital resources, student digital competence facilitation and professional engagement are the strongest evidence-based capability areas. These findings should be read as planning signals, not as proof of CI adoption. Teacher and faculty digital-competence studies support the relevance of these domains while also showing that competence varies across profiles, contexts, readiness levels and development pathways (Aydin et al., 2024; Cabero-Almenara et al., 2020; Falloon, 2020; Lucas et al., 2021; Scherer et al., 2021; Tondeur et al., 2021).

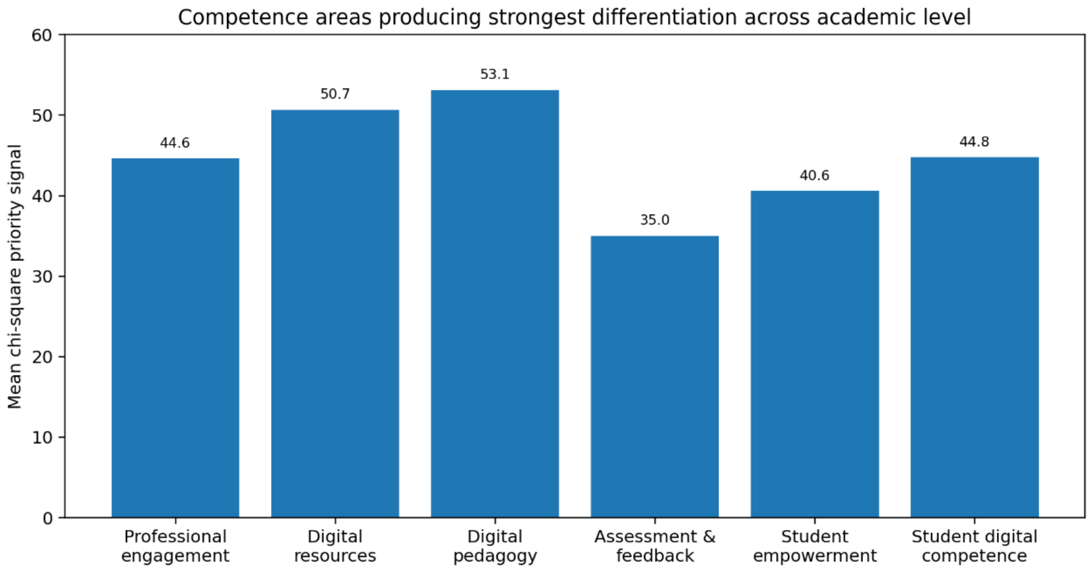

Figure 3. Domain-level priority signals derived from reported item-level chi-square values

Table 8. Competence Areas and CI-Based Development Implications

Competence area	Mean priority signal	CI interpretation	Development implication
Digital pedagogy	53.14	Strongest capability-gap signal.	Prioritize digital lesson design, collaboration and student self-regulation support.
Digital resources	50.68	High practical relevance for capability development.	Support resource curation, content creation, licensing and data protection.
Student digital competence facilitation	44.77	Important for employability and digital citizenship.	Train faculty to embed information evaluation, communication and safe digital behavior.
Professional engagement	44.63	Signals variation in collaboration and continuous learning.	Promote communities of practice, webinars and mentoring.
Student empowerment	40.60	Moderate signal with inclusion value.	Develop inclusive digital tasks and personalized pathways.
Assessment and feedback	35.04	Lower mean signal but strategically sensitive.	Strengthen formative feedback and ethical analytics use.

4.4 Predictive Evidence as Diagnostic Intelligence

The discussion of machine learning indicators is limited to being diagnostic intelligence indicators. It is not the goal of a technical presentation to compare algorithms. The higher the AUC value, the more evidence is available to differentiate certain competence levels; the lower the value, the more evidence is needed for decision makers to seek qualitative follow-up, peer consultation, or additional organizational evidence. There are, therefore, two ways of interpreting Figures 4 and Table 9: one involving the use of decisions, and the other computational performance. Such a conservative approach echoes recent research in education predictive modelling and learning analytics, which emphasises that analytics be used for guiding decisions in context rather than as a prescription (Almalawi et al., 2024; Ifenthaler & Yau, 2020).

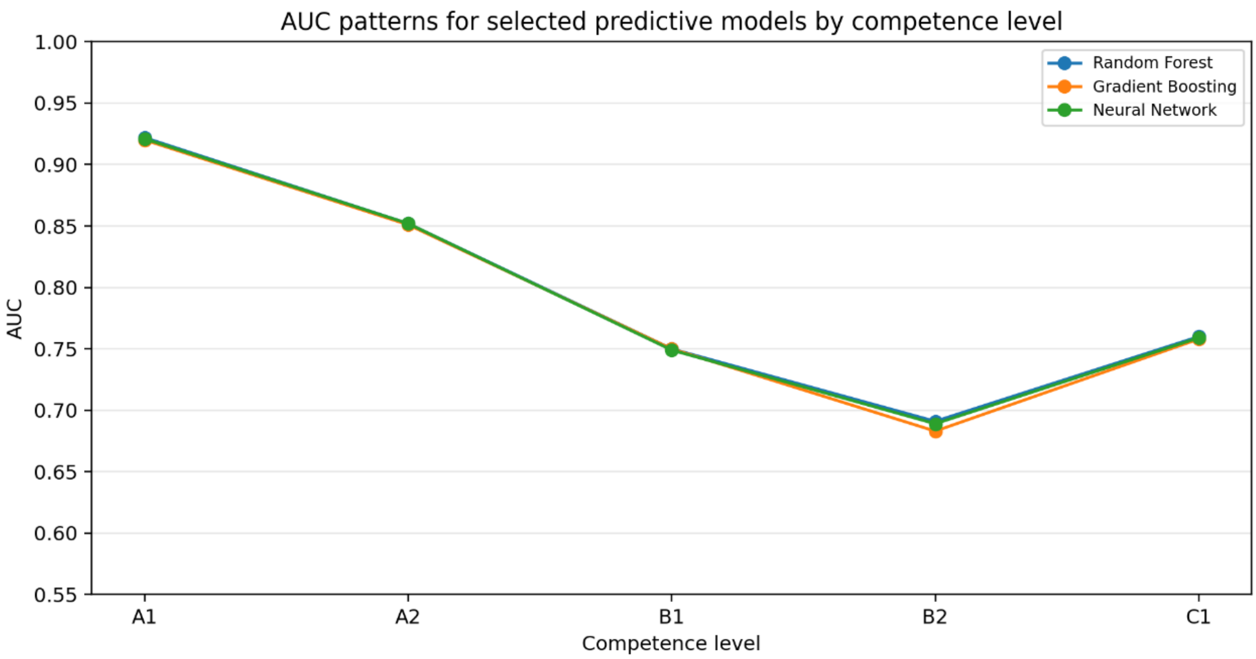

Figure 4. AUC patterns for selected models across faculty competence levels

Table 9. Predictive Evidence Interpreted as Diagnostic Intelligence

Competence level	Random Forest AUC	Gradient Boosting AUC	Neural Network AUC	CI-based interpretation
A1 Newcomer	0.922	0.920	0.921	High discrimination should be combined with careful foundational diagnosis.
A2 Explorer	0.852	0.851	0.852	Supports early segmentation for targeted support.
B1 Integrator	0.750	0.750	0.749	Suggests need for differentiated development pathways.
B2 Expert	0.691	0.683	0.689	Requires richer contextual indicators before strategic decisions.
C1 Leader	0.760	0.758	0.759	Can support mentoring and innovation roles after contextual confirmation.

4.5 Proposed Observable Indicators for Sustainable Competitive Advantage

This is a secondary study in which sustainable competitive advantage is not measured empirically. The revised manuscript does not include conceptual overclaiming; instead, it outlines observable indicators that validate the manuscript in the future at institutional level. Table 10 also makes it clear that these are suggested KPIs to be applied in the future, not measured from the current data set. The KPI logic is provided because recent research in competitive intelligence and in digital transformation (Ibrahim et al., 2025; Verhoef et al., 2021) has demonstrated that there are measurable organizational outcomes related to the use of intelligence as well as to capability renewal and sustainable competitiveness, and not just to conceptual discussion.

Table 10. Proposed KPIs for Future Measurement of Sustainable Competitive Advantage

CI output	Observable future KPI	Sustainable advantage logic
Capability-gap intelligence	Percentage of priority gaps addressed through approved development plans.	Links sensing to resource allocation.
Strategic HRM translation	Training completion, mentoring participation and micro-credential uptake.	Turns intelligence into capability-building action.
Knowledge dissemination	Number of intelligence briefs, repository items, communities of practice and reuse events.	Converts individual knowledge into organizational learning.
Decision governance	Number of documented decisions based on intelligence briefs and follow-up reviews.	Creates repeatable evidence-based governance.
Post-intervention capability movement	Pre/post competence shifts and department adoption rates.	Shows whether CI-informed action produces capability improvement.
Strategic foresight use	Number of foresight notes included in planning cycles.	Connects current capability evidence to future institutional readiness.

4.6 CI Governance Architecture and Future Validation

The revised governance architecture centers on responsibility, dissemination and feedback. A university applying the framework should establish a small CI steering group, define intelligence needs, produce decision briefs, disseminate them to responsible units and document decisions. The framework should then be validated through the protocol in Table 6 before claims of organizational effectiveness are made. Figure 5 illustrates the governance logic. The figure should be read as a validation-ready architecture, not as evidence that the architecture has already been empirically tested.

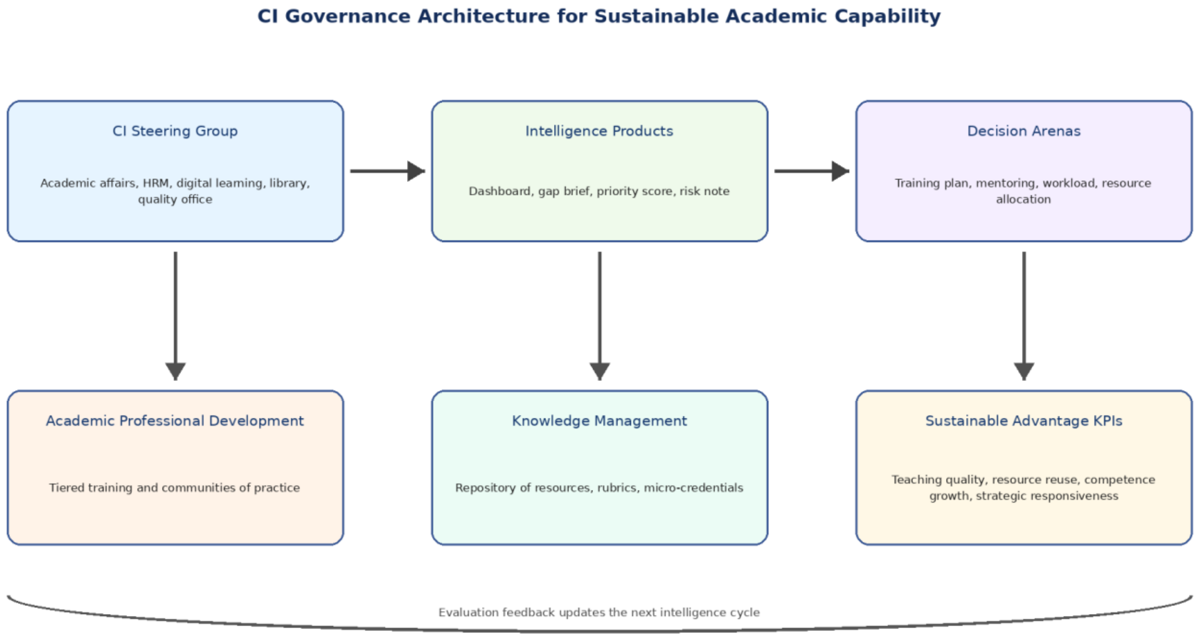

Figure 5. Validation-ready CI governance architecture for sustainable academic capability

4.7 Discussion of Contribution and Boundary of Claims

Theoretical and methodological contributions are the main contributions. The article provides input on Sustainable Competitive Intelligence by defining how capability evidence can be turned into an intelligence product, dissemination routines, governance responsibilities, and future KPIs by an academic institution. Another methodological boundary it provides is for secondary-data research: evidence can contribute to the building of the framework, but cannot supplant primary organisational validation. The academic capability domain remains important, as recent studies also demonstrate correlations between lecturers' digital competence and learning value, professional readiness, and the need for institutional capability in higher education (Crompton & Burke, 2023; Dang et al., 2024; Tee et al., 2024). The article thus does not claim the direct measurement of CI or the direct measurement of sustainable competitive advantage, nor does it measure the results of the Delphi/AHP validation or the actual KPI outcomes. These restrictions are not concealed. They are embedded in the revised design and provide the opportunity for future studies to be built on through interviews, expert panels, case studies and longitudinal organizational evaluation.

5 FINAL CONSIDERATIONS

The present study proposed a framework of Sustainable Competitive Intelligence for academic capability development which is ready to be validated. The public faculty competence dataset makes it possible to trace the evidence input, however, the study does not directly make the public faculty competence itself a measure of CI adoption and sustainable competitive advantage. The new article focuses on the role of CI in the center: environmental scanning, competitive sensing, intelligence networks, strategic foresight, governance, dissemination and decision use. The study being presented overcomes the primary methodological weakness of not collecting primary data, and that the framework needs to be validated with organisations in the future. Delphi/AHP and KPI are not listed as completed procedures, but as required future validation steps. This ensures transparency of the article, avoiding false claims and thus the study is in line with the epistemological requirements of Sustainable Competitive Intelligence. Further studies should carry out primary data collection from the managers of the University, the leaders of faculty development, HRM units, quality assurance teams, and knowledge management actors. It should implement Delphi or AHP process to validate the weights of CPI, test the usefulness of intelligence products, and then carry out case studies of the implementation of CI governance, measure the longitudinal KPI outcomes after interventions.

5.1 Data Availability Statement

The dataset used as an evidence input is publicly available on Figshare: Moreira Choez, J. S., Nunez-Naranjo, A. F., Carrasco Valenzuela, A. C., Lopez-Lopez, H. L., Vazquez Meza, J. A., and Sabando-Garcia, A. R. (2025). Data from the article titled Machine Learning Algorithms to Predict Digital Competencies in University Faculty [Data set]. Figshare. https://doi.org/10.6084/m9.figshare.29036066.v1.

5.2 Ethics Statement

This study did not require new recruitment, new data collection or direct contact with human participants because it used an existing anonymized public dataset. The secondary analysis was conducted by citing the dataset source, avoiding re-identification and limiting claims to the available evidence.

5.3 Funding, Conflict of Interest and Author Contributions

Funding: This research received no external funding. Conflict of interest: The authors declare no conflict of interest. Author contributions: Conceptualization: Author 1; methodology: Author 1 and Author 2; data source identification and curation: Author 1 and Author 2; formal analysis and interpretation: Author 1; writing-original draft: Author 1; writing-review and editing: Author 2 and Author 3; supervision: Author 3. All authors have read and agreed to the final version of the manuscript.

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