Student Persistence as Academic Intelligence: An Integrationist Learning Analytics Framework for Higher Education

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Abstract

Student persistence remains a major challenge in higher education worldwide, particularly in contexts marked by expansion, diversification, and persistent inequalities. Although previous research has generated important insights into student engagement, integration, and retention, many approaches remain limited in their ability to account for the systemic, dynamic, and data-rich conditions that shape contemporary higher education.

This article proposes a theoretical-methodological framework that reconceptualizes student persistence as a form of institutional intelligence. Grounded in the MIPESA model, which understands persistence as an emergent outcome of interactions among institutional management, course quality, teaching practice, and student engagement, the study proposes an integrative architecture that connects theory, analytics, and institutional action.

More specifically, the article introduces the Student Persistence Index (IPE-PESA), a multidimensional analytical model designed to support the early identification of students at risk through the integration of academic, behavioral, and contextual data. It also develops the concept of Academic Persistence Intelligence (API), through which predictive analytics, institutional interventions, and continuous evaluation are linked within a systemic decision-making framework. In addition, the study incorporates a territorial dimension through Atlas PESA, enabling the identification of spatial patterns of student vulnerability and supporting context-sensitive institutional responses.

By integrating educational theory, learning analytics, and institutional strategy, the article contributes to current debates on student persistence and student success by offering a scalable and conceptually grounded framework for proactive, evidence-informed action in higher education.

Keywords: student persistence; student retention; learning analytics; higher education; academic intelligence

Introduction

Student persistence has become one of the most pressing challenges in contemporary higher education systems worldwide. Despite substantial progress in widening access, dropout and non-completion remain persistent phenomena, especially among students from socioeconomically disadvantaged backgrounds (Thomas, 2012; Yorke, 2004; Cabrera, Nora and Castañeda, 1993). This persistent gap between access and successful completion reveals a structural tension within higher education: efforts toward democratization have not always been accompanied by equally effective strategies to support continuity, progression, and degree completion (Marginson, 2016; Altbach, Reisberg and de Wit, 2019).

Over the past decades, research on student persistence has been strongly shaped by theoretical models that emphasize the relationship between students and institutional environments. Tinto's (1975, 1993) framework conceptualizes persistence in terms of academic and social integration; Astin (1984) highlights the centrality of student involvement; and Kuh (2008) underscores the importance of engagement and institutional conditions. Other contributions, such as Bean (1980) and Braxton, Milem and Sullivan (2000), have further expanded the field by incorporating psychological and organizational dimensions.

Although these perspectives have significantly advanced the understanding of student persistence, they are less effective in addressing the complexity of contemporary higher education systems, particularly in contexts marked by inequality, institutional heterogeneity, and rapid digital transformation. In many cases, they rely on relatively linear and individual-centered explanations, underrepresent systemic interactions, and offer limited pathways for institutional operationalization (Zepke and

Leach, 2010; Thomas, 2012). As higher education becomes increasingly data-intensive, diverse, and dynamic, there is a growing need for frameworks capable of explaining persistence as a multidimensional process while also supporting actionable institutional strategies.

At the same time, the emergence of learning analytics has opened new possibilities for understanding and predicting student trajectories through data (Siemens and Long, 2011; Ferguson, 2012; Gašević, Dawson and Siemens, 2015). By identifying patterns of engagement, performance, and risk, learning analytics has encouraged more data-informed institutional practices. However, many of these developments remain predominantly technical, often lacking stronger theoretical grounding and a more consistent connection between data analysis and institutional decision-making (Knight, Buckingham Shum and Littleton, 2014). In addition, an excessive focus on indicators and quantitative outputs may obscure the relational, pedagogical, and contextual dimensions that are constitutive of educational processes. Taken together, these limitations reveal the need for scalable frameworks capable of integrating theory, analytics, and institutional action.

This article addresses that gap by proposing the PESA Academic Intelligence Framework, grounded in the MIPESA model (Kohls-Santos, 2025). The central argument is that student persistence should be reconceptualized as a form of institutional intelligence: a dynamic and strategic process through which institutions continuously generate, interpret, and act upon evidence in order to support student trajectories. From this perspective, persistence is not treated as the product of isolated individual factors, but as an emergent outcome of interactions among institutional management, course quality, teaching practice, and student engagement.

Building on this theoretical foundation, the article contributes to the field in three ways. First, it repositions MIPESA as a systemic and integrationist framework for understanding student persistence in contemporary higher education. Second, it operationalizes this perspective through the Student Persistence Index (IPE-PESA) and the concept of Academic Persistence Intelligence (API), linking predictive analytics, institutional intervention, and continuous evaluation. Third, it incorporates a territorial dimension through Atlas PESA, expanding the framework's capacity to identify spatial patterns of student vulnerability and to support more context-sensitive institutional responses.

By articulating educational theory, learning analytics, and institutional strategy, the article contributes to current debates on student success and offers a conceptually grounded framework for proactive and evidence-informed action in higher education.

Theoretical Framework

Student Persistence in Higher Education: From Integration to Complexity

Research on student persistence has long been guided by theoretical models that seek to explain why students remain in or withdraw from higher education. Among the most influential contributions, Tinto's (1975, 1993) model conceptualizes persistence as a function of academic and social integration, suggesting that students who establish stronger connections with institutional life are more likely to continue their studies. This perspective underscores the importance of institutional environments, peer interaction, and academic systems in shaping student trajectories.

Complementing this view, Astin's (1984) theory of student involvement introduces a behavioral dimension by arguing that persistence is closely related to the quantity and quality of students' investment in educational experiences. Similarly, Kuh

(2008) expands the discussion through the concept of student engagement, emphasizing institutional practices that promote active learning, participation, and meaningful educational experiences. Additional contributions, such as Bean (1980) and Braxton, Milem and Sullivan (2000), further broaden the field by incorporating psychological and organizational dimensions into the analysis of student departure.

Although these approaches have made important contributions, they also share limitations when examined in light of contemporary higher education systems. First, they tend to privilege individual and relational explanations while giving less attention to structural and systemic conditions. Second, they were largely formulated in more stable institutional contexts and therefore offer limited explanatory power in increasingly heterogeneous, unequal, and rapidly changing educational environments. Third, they do not offer sufficiently robust mechanisms for direct operationalization within data-driven institutional systems.

More recent scholarship has called for more expansive and theoretically sophisticated understandings of student persistence (Zepke and Leach, 2010; Thomas, 2012). Within this line of inquiry, persistence is no longer conceived as the outcome of isolated or linearly associated variables, but as a socially and institutionally mediated phenomenon that emerges through the interaction of individual dispositions, institutional arrangements, and broader structural conditions. In the case of online students, Rutledge, Chukwuma, Simonetti and Sam (2026) further reinforce this interpretation by demonstrating that persistence is significantly shaped by situational and dispositional factors. Taken together, these contributions signal an important epistemological reorientation: away from reductionist and individualizing explanations and toward a more relational, contextual, and structurally informed understanding of student persistence in contemporary higher education.

The Emergence of Learning Analytics

The expansion of digital technologies and data-intensive systems has contributed to the emergence of learning analytics as a relevant field for understanding and predicting student trajectories. In general terms, learning analytics involves the collection, analysis, and interpretation of educational data with the purpose of informing decision-making and improving learning processes and student outcomes (Siemens and Long, 2011; Ferguson, 2012; Mougiakou, Vinatsella, Sampson, Papamitsiou, Giannakos and Ifenthaler, 2023).

By analyzing digital traces such as interactions in learning management systems, assessment performance, participation patterns, and attendance records, institutions can identify early warning signs of disengagement and academic risk. This predictive potential represents an important shift in higher education, making it possible to move from reactive responses to more proactive and preventive approaches to student support (Delgado-García, Fernández-Rey, Álvarez-Pérez and López-Aguilar, 2026).

However, despite its analytical potential, learning analytics also presents important limitations. Many models remain predominantly technical and are not sufficiently grounded in educational theory, which can lead to fragmented or overly context-specific applications. In some cases, analytics systems focus on isolated indicators, such as grades or login frequency, without accounting for the multidimensional conditions under which persistence occurs. In addition, a persistent gap often remains between data analysis and institutional action, which reduces the practical effectiveness of analytics in supporting meaningful and timely intervention.

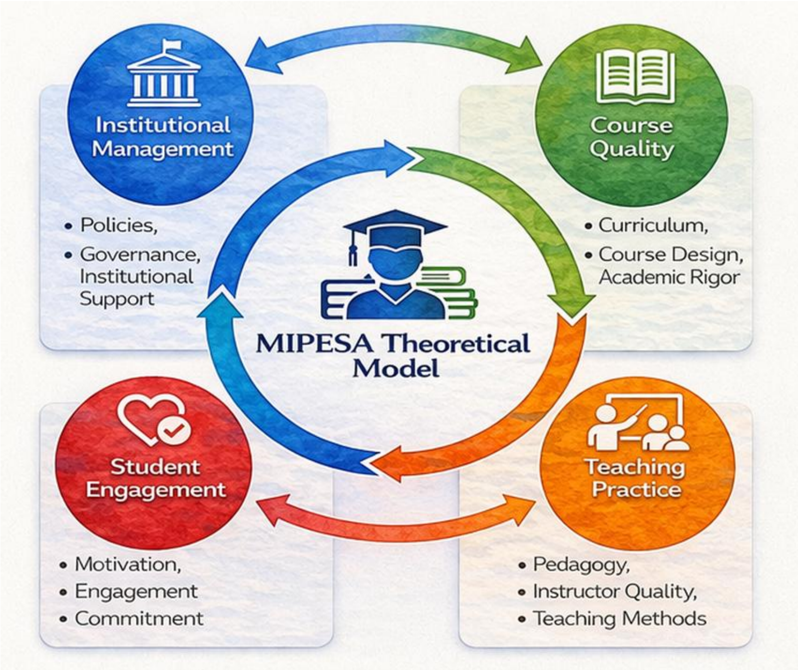
These limitations indicate that learning analytics, on its own, is insufficient to explain and address the complexity of student persistence. What is needed are frameworks capable of integrating data analysis with theoretically grounded and institutionally actionable models of student persistence and student success.

MIPESA as an Integrationist Theoretical Model

In response to these limitations, the MIPESA model (Kohls-Santos, 2025) is proposed as a central theoretical framework for advancing a systemic and integrationist understanding of student persistence. Rather than treating persistence as the consequence of isolated variables, MIPESA conceptualizes it as an emergent property of interactions among four interdependent dimensions:

- Institutional Management: encompassing policies, governance structures, institutional support systems, and strategic decision-making processes;
- Course Quality: including curriculum design, academic coherence, learning pathways, and the rigor of educational programs;
- Teaching Practice: referring to instructional approaches, teacher engagement, feedback processes, and pedagogical innovation;
- Student Engagement: involving motivation, participation, commitment, time investment, and behavioral involvement in learning activities.

Figure 1. MIPESA Theoretical Model



Source: Author's own elaboration, based on the MIPESA model (Kohls-Santos, 2020; 2025).

Figure 1 presents the MIPESA theoretical model as an integrationist framework for understanding student persistence and academic success. The model is organized around four core and interdependent dimensions: Institutional Management, Course Quality, Teaching Practice, and Student Engagement.

The model assumes that these dimensions do not operate in isolation. Rather, they interact continuously and reciprocally, producing the conditions that support or undermine student persistence. By integrating academic, institutional, relational, and contextual factors, MIPESA advances beyond traditional explanatory models and provides the conceptual basis for the development of analytical and technological structures such as PESA and the IPE-PESA.

A key contribution of MIPESA lies in its integrationist perspective. Rather than being treated as separate domains, these dimensions interact continuously and bidirectionally. From this perspective, persistence is not the result of isolated academic, institutional, or individual factors; rather, it emerges from the dynamic interplay among these dimensions across the student trajectory.

MIPESA does not reject classical theories of persistence. Instead, it extends them by incorporating Tinto's emphasis on integration, Astin's focus on involvement, and Kuh's engagement framework within a broader systemic structure. In this sense, MIPESA may be understood as a second-generation theoretical model: one that not only explains student persistence conceptually, but also creates the conditions for its analytical and institutional operationalization.

It is important to note that MIPESA is grounded in longitudinal research conducted across 12 institutions in two countries, which strengthens its relevance as a theoretically informed and empirically sustained framework for understanding persistence in diverse higher education contexts.

Academic Persistence Intelligence: From Theory to Institutional Action

Building on the MIPESA model, this article advances the concept of Academic Persistence Intelligence (API) as the operational extension of the theoretical framework into institutional practice. API is defined as a systemic approach that integrates theory, analytics, and institutional decision-making in order to support student persistence through continuous cycles of identification, intervention, monitoring, and evaluation (Williamson, 2017; Selwyn, 2019).

API is structured around three interrelated layers:

- The first is the theoretical layer, grounded in MIPESA and in the broader literature on student persistence;
- The second is the analytical layer, based on learning analytics and predictive modeling;

- The third is the institutional layer, focused on decision-making, intervention design, and policy implementation;
- Taken together, these layers transform persistence from a descriptive concept into an actionable institutional process.

From this perspective, persistence is no longer treated as an outcome to be measured only retrospectively. Instead, it becomes a dynamic process that institutions can actively monitor, interpret, and manage in real time. API therefore adds a strategic dimension to student persistence by positioning it at the center of institutional governance and academic intelligence.

This framework advances the field by helping bridge the gap between conceptual explanation and institutional action. It provides the basis for the development of analytical tools such as the Student Persistence Index (IPE-PESA) and for the implementation of institutional systems such as Atlas PESA, which together enable data-informed decision-making and context-sensitive intervention in higher education.

In this sense, MIPESA not only integrates existing theoretical traditions, but also shifts the analytical focus of student persistence from individual trajectories to systemic interactional processes. Building on this theoretical foundation, the following section presents the methodological structure of the PESA framework and explains how these constructs are operationalized through data integration, predictive modeling, and learning analytics.

Methodology

Research Design and Epistemological Positioning

This article adopts a quantitative, analytical, and model-development design aimed at operationalizing a theoretical framework for student persistence within data-rich institutional environments. The methodological approach is based on the assumption that student persistence is a multidimensional and dynamic phenomenon that can be analytically modeled through the integration of heterogeneous institutional data sources.

From an epistemological perspective, the study is aligned with a post-positivist and systems-oriented approach. This position recognizes that student persistence cannot be reduced to deterministic causal variables, while also assuming that probabilistic patterns, multidimensional risk configurations, and institutional trends can be identified through structured analytical procedures. Such a perspective allows the articulation of theoretical constructs derived from MIPESA with measurable indicators generated in institutional contexts.

The aim of the methodology is not to establish causal inference in an experimental sense, but to develop a theoretically grounded analytical structure capable of classification, prediction, and institutional application. Accordingly, the methodological design prioritizes construct validity, analytical coherence, and operational feasibility.

Conceptual Operationalization: From MIPESA to IPE-PESA

The operationalization of the MIPESA model is conducted through the development of the Student Persistence Index (IPE-PESA), a composite analytical indicator designed to estimate the likelihood of student persistence based on multiple institutional and educational dimensions.

The index translates the four dimensions of MIPESA into measurable analytical domains, each associated with specific variables and data sources.

Table 1. Operationalization of the MIPESA Dimensions in the IPE-PESA Model.

MIPESA Dimension	Analytical Variables	Data Sources
Institutional Management	Access to support services, financial status, institutional participation	Financial records; student support services records
Course Quality	Course structure, academic progression, curricular organization	Academic records
Teaching Practice	Instructor-student interaction, participation in course-based learning activities	Learning Management System (LMS)
Student Engagement	Attendance, activity completion, behavioral engagement, extra-class participation	Learning Management System (LMS); attendance systems

Through this structure, theoretical constructs are converted into measurable indicators that can be aggregated within a multidimensional model. The selection of variables follows two complementary criteria: theoretical alignment with the MIPESA framework and institutional relevance for the identification of patterns associated with student persistence.

Rather than reducing persistence to a single factor, this operationalization preserves its multidimensional character and creates the analytical basis for classification, monitoring, and institutional decision-making.

Data Integration and Processing

The proposed analytical structure integrates data from multiple institutional sources in order to capture different dimensions of student persistence. These sources include the following:

- Learning Management Systems (LMS);
- academic records, including grades, progression, and enrollment status;
- attendance systems;
- financial and administrative records;
- programmatic and support-service data.

Data integration is conducted through a unified analytical layer designed to ensure consistency, interoperability, and scalability across heterogeneous institutional datasets (see Figure 2).

Figure 2. PESA System Architecture

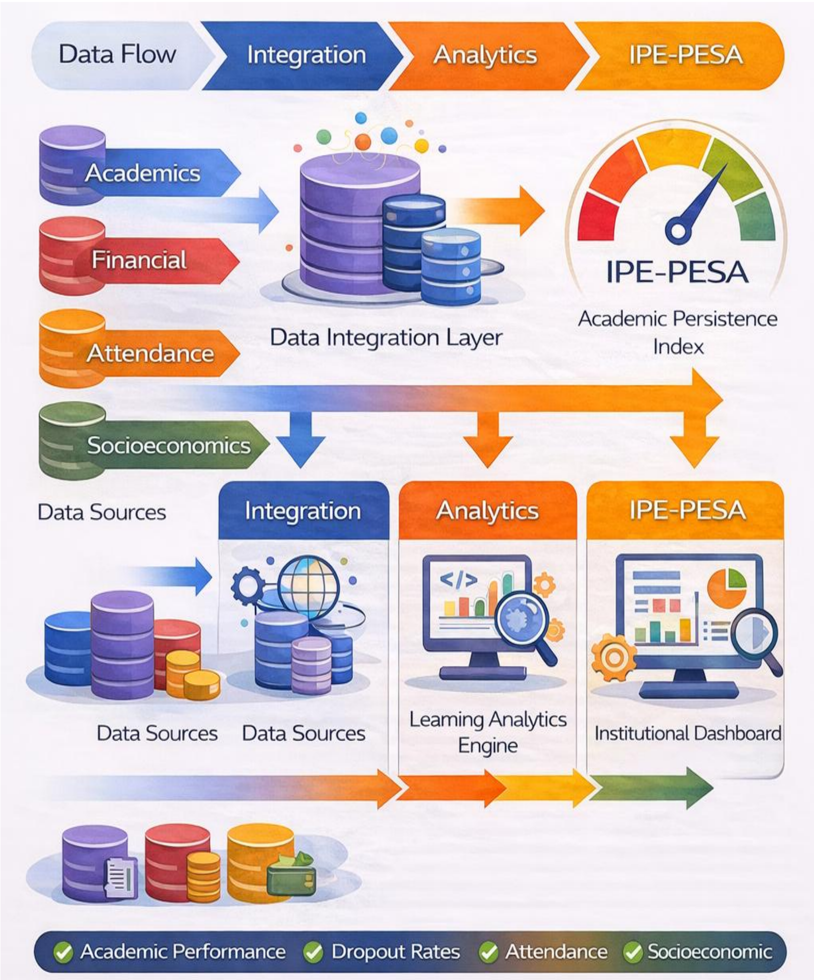


Figure 2 illustrates the analytical architecture of the PESA system and shows how multiple institutional data sources are integrated and transformed into academic intelligence. The architecture begins with a data layer composed of academic, financial, attendance, and socioeconomic information. These heterogeneous inputs are then consolidated through a data integration layer, enabling standardization and interoperability across institutional systems.

The integrated data are subsequently processed through a learning analytics engine that supports predictive modeling, engagement analysis, and risk detection. The central analytical output of this process is the Student Persistence Index (IPE-PESA), which synthesizes multiple indicators into a single multidimensional score associated with the likelihood of student persistence.

The outputs are then displayed through institutional dashboards and alert systems that provide decision-makers with timely information for monitoring student trajectories and planning interventions. In this sense, the PESA architecture supports a shift from descriptive analytics toward predictive and decision-oriented analytics in higher education.

To ensure comparability across variables, all indicators are normalized to a common 0–1 scale prior to aggregation. Depending on the distribution and nature of the data, normalization procedures may include min–max scaling or standardized transformations. Missing data are treated through predefined analytical rules, including imputation or exclusion, according to their frequency, relevance, and impact on model stability.

Construction of the IPE-PESA Index

The IPE-PESA is defined as a weighted composite index that aggregates the standardized scores of each MIPESA dimension into a single persistence score ranging from 0 to 1, where higher values indicate a greater likelihood of student persistence.

The general formulation of the index is:

$$IPE - PESA_i = \sum_{d} \left(w_d \cdot S_{\{id\}}\right)$$

where:

- *IPE-PESA*$_i$ represents the persistence score of student *i*.

- w_{d} represents the weight assigned to dimension d.
- S_{id} represents the standardized score of student i in dimension d.

All variables are first transformed to a common metric before aggregation. This procedure ensures comparability across indicators derived from different institutional sources and measured on different scales. When appropriate, min–max normalization is applied using the following formula:

$$X' = \frac{X - X_{\{min\}}}{X_{\{max\}} - X_{\{min\}}}$$

- X' represents the normalized value.
- X represents the observed value of the variable.
- X_{min} represents the minimum observed value.
- X_{max} represents the maximum observed value.

The weighting structure of the index may follow three complementary approaches.

- **Theoretical weighting** which assigns weights according to the conceptual centrality of each dimension within the MIPESA model.
- **Empirical weighting** which derives weights from statistical procedures, such as regression analysis or factor analysis, based on the contribution of each dimension to the prediction of student persistence.
- **Institutional calibration**, which allows the adjustment of weights according to contextual priorities, historical data, and local policy objectives.

This flexible weighting strategy allows the model to be adapted to different institutional realities while preserving theoretical coherence. Rather than prescribing a single universal weighting scheme, the IPE-PESA is designed as a context-sensitive analytical structure that supports local implementation within a shared conceptual framework.

Risk Classification Model

Based on the IPE-PESA score, students are classified into four risk levels that support differentiated institutional responses:

Figure 3. PESA Risk Classification Model

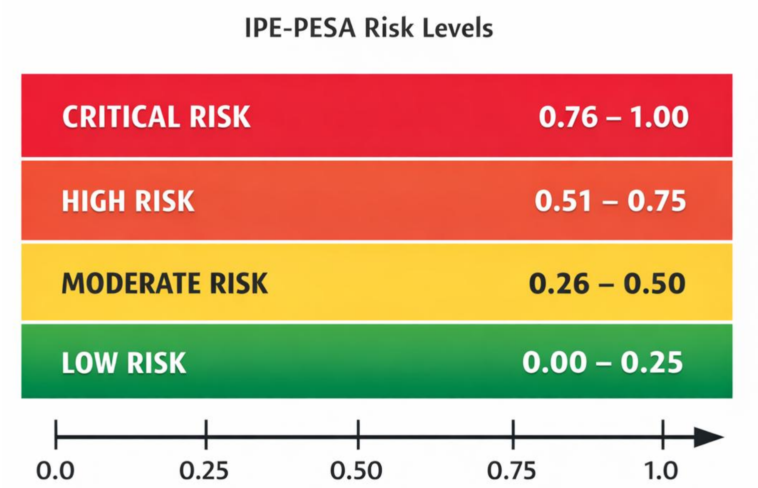


Figure 3 presents the PESA Risk Classification Model, which categorizes students into four levels of risk according to their IPE-PESA scores: Critical Risk, High Risk, Moderate Risk, and Low Risk. Each category corresponds to a different degree of vulnerability and is associated with specific institutional responses.

Students classified as Critical Risk require immediate and intensive support, including structured mentoring, individualized tutoring, psychosocial follow-up, or financial assistance when relevant. Students classified as High Risk benefit from targeted academic advising and individualized monitoring strategies aimed at preventing further disengagement. Students classified as Moderate Risk may be supported through group-based interventions, such as study-skills workshops, collaborative tutoring, and engagement reinforcement strategies. Students classified as

Low Risk, while not in immediate danger, should remain connected to preventive and developmental actions that sustain their academic trajectory.

This classification model enables institutions to prioritize interventions, allocate resources strategically, and tailor responses according to student profiles. By linking predictive analytics to actionable categories, the system strengthens institutional capacity for proactive and context-sensitive responses to academic risk.

Analytical Validation Strategy

Given the model-development nature of this study, the validation strategy is analytical and simulation-based rather than large-scale empirical. Synthetic student profiles are used to represent different combinations of conditions across the MIPESA dimensions, allowing the internal behavior of the model to be examined under distinct risk configurations.

The validation procedure focuses on three main analytical criteria:

- **Sensitivity:** the ability of the model to detect variations across student profiles;
- **Differentiation:** the capacity of the model to classify students into distinct risk categories;
- **Internal consistency:** the coherence between the theoretical dimensions of MIPESA and the analytical outputs generated by the index.

The results of this analytical testing suggest that the IPE-PESA is capable of distinguishing multidimensional patterns of vulnerability and of producing differentiated classifications consistent with the theoretical assumptions of the model.

It is important to note, however, that this stage does not constitute full empirical validation in large-scale institutional settings. Rather, it provides an initial analytical verification of model coherence and applicability, establishing a foundation for future empirical testing, calibration, and cross-institutional implementation.

Ethical Considerations

The use of educational data in learning analytics raises significant ethical questions concerning privacy, data protection, fairness, and the institutional consequences of predictive classification in higher education. Although the present study does not involve the empirical use of real student data, the framework proposed here is informed by a data ethics perspective that treats predictive systems not as neutral technical instruments, but as socio-technical arrangements with normative implications for institutional decision-making.

From this standpoint, any future implementation of the proposed model should be guided by principles of transparency, accountability, proportionality, and student-centered use. In practice, this means that educational data should be mobilized only for purposes of academic support and educational improvement; that appropriate safeguards should be adopted to protect student identity and data integrity; and that predictive classifications should not be used to penalize, stigmatize, or naturalize vulnerability. Rather, such systems should function as instruments for identifying conditions that call for more careful, equitable, and context-sensitive institutional support.

The framework is therefore aligned with contemporary debates in ethical learning analytics that emphasize responsible data governance, the situated character of predictive interpretation, and the obligation to ensure that institutional analytics remain pedagogically defensible, socially responsive, and ethically accountable.

Methodological Contribution

The methodological contribution of this study lies in the integration of three components:

- a theoretical model (MIPESA);
- an analytical index (IPE-PESA);
- an institutional intelligence framework (API).

Taken together, these components form a theoretically grounded and operationally adaptable structure for analyzing and supporting student persistence in higher education. Rather than treating theory, analytics, and institutional action as separate domains, the proposed methodology connects them within a single framework.

This integration moves beyond isolated methodological approaches by offering a replicable and context-sensitive model that combines theoretical alignment with analytical applicability. In this sense, the methodological contribution of the article lies not only in the construction of an index, but also in the articulation of a broader analytical architecture capable of supporting decision-making, intervention planning, and future empirical implementation.

Results and Discussion

Multidimensional Configurations of Student Persistence

The analytical results developed in this study suggest that student persistence cannot be adequately understood through isolated variables or linear relationships alone. Rather, the model points to multidimensional configurations of risk in which vulnerabilities accumulate and interact across different domains of the student experience. In this sense, risk is better understood as configurational rather than merely additive, reinforcing the relevance of systemic analytical approaches.

Students classified in the higher-risk categories (Critical Risk and High Risk) tend to present simultaneous fragilities across more than one MIPESA dimension. These configurations typically combine low levels of engagement in learning environments, weaker academic performance, and indicators of financial or institutional disconnection. This pattern is consistent with the central proposition of MIPESA, according to which persistence emerges from interactions among institutional, academic, and behavioral factors.

By contrast, students in the lower-risk categories tend to display more balanced performance across dimensions. Rather than excelling in only one area, these students generally present moderate to high levels of engagement, more stable academic performance, and more consistent interaction with institutional structures. This pattern reinforces the interpretation of persistence as a systemic and multidimensional phenomenon.

Taken together, these results challenge reductionist explanations that attribute dropout primarily to individual characteristics or to isolated institutional variables. They instead support the need for integrated analytical frameworks capable of capturing the complexity of student trajectories in higher education.

Predictive Capacity and Early Identification of Risk

One of the main analytical contributions of the IPE-PESA model lies in its capacity to support the early identification of students exposed to higher levels of academic risk. By integrating multiple variables into a single composite index, the model enables institutions to detect multidimensional patterns of vulnerability before they translate into academic failure, disengagement, or dropout.

This analytical capacity supports a shift from reactive institutional responses—typically activated only after substantial academic decline—toward more anticipatory and preventive strategies informed by timely data analysis (see Figure 4). From this perspective, student persistence becomes a process that institutions can actively monitor and support, rather than merely observe retrospectively.

Figure 4. PESA Intervention Impact Framework

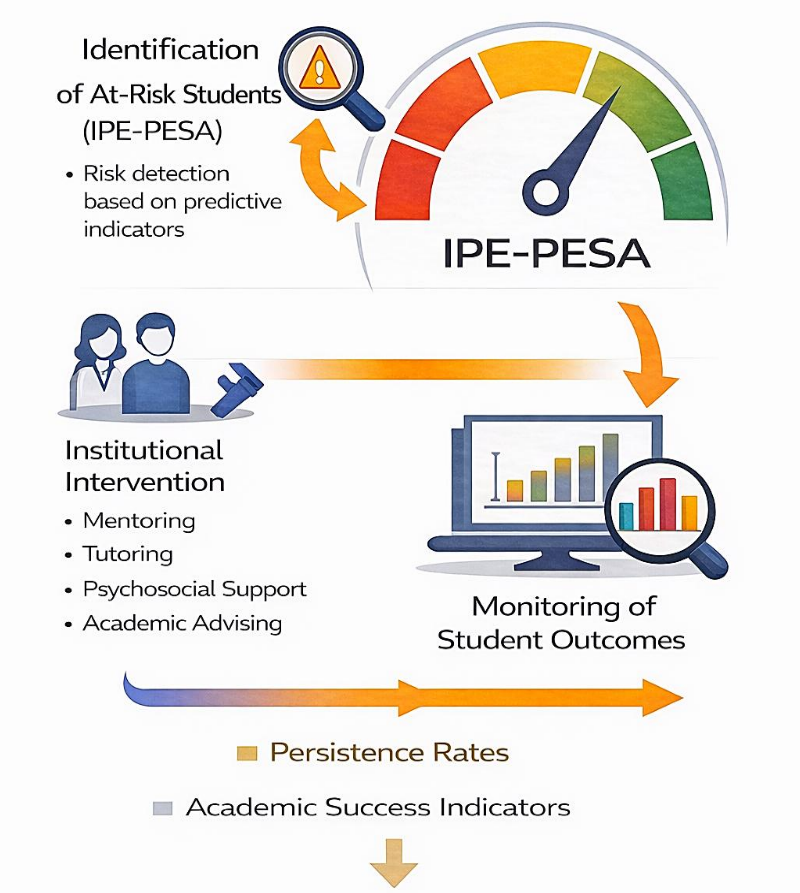


Figure 4 illustrates the PESA Intervention Impact Framework, which conceptualizes student persistence as a continuous and iterative process connecting predictive analytics, institutional action, and outcome evaluation. The framework begins with the identification of at-risk students through the Student Persistence Index (IPE-PESA), which aggregates indicators related to academic performance, engagement, attendance, and contextual vulnerability. Based on this identification, institutions may implement targeted interventions, including mentoring, tutoring, psychopedagogical support, and academic advising.

Following intervention, the framework includes a structured phase for monitoring student outcomes, focusing on indicators such as engagement levels, academic performance, and attendance patterns. These outcomes can then be examined in order to assess the impact of institutional actions through indicators such as persistence rates and academic success metrics.

A central feature of the model is its feedback loop, which enables institutions to continuously assess the effectiveness of their actions and refine policies and strategies accordingly. By connecting prediction, intervention, and evaluation, the framework transforms institutional data into actionable intelligence and strengthens the institutional capacity for evidence-informed decision-making.

The classification of students into risk categories also allows for the prioritization of institutional action, supporting more efficient resource allocation and interventions tailored to the needs of different student groups. In this sense, the model aligns with recent discussions in learning analytics that advocate moving beyond prediction toward actionable and institutionally embedded forms of intelligence.

From Learning Analytics to Academic Persistence Intelligence

The integration of the IPE-PESA model within institutional systems gives rise to what this study conceptualizes as Academic Persistence Intelligence (API). This concept extends traditional learning analytics by establishing a structured connection between data analysis, institutional action, and continuous monitoring.

Rather than functioning as a standalone analytical tool, the PESA framework operates as an integrated intelligence system characterized by continuous feedback loops linking prediction, intervention, monitoring, and evaluation. In this configuration, analytics is not an end in itself, but part of a broader institutional process oriented toward supporting student persistence.

The articulation of these components supports the development of alert systems, intervention monitoring mechanisms, and policy support tools. By linking theoretical constructs with analytical models and practical applications, the framework establishes a more comprehensive approach to academic intelligence in higher education.

In this sense, the proposed model contributes to the field by integrating educational theory, data analytics, and institutional strategy within a single framework. The feedback loop at the center of API transforms data into institutional learning, enabling the continuous refinement of strategies, policies, and decision-making processes related to student persistence.

Territorial Dimension and the Atlas PESA

A key innovation of the proposed model lies in the incorporation of a territorial dimension, operationalized through Atlas PESA, which enables the identification of spatial patterns of student vulnerability and supports geographically oriented institutional interventions (see Figure 5).

Figure 5. Atlas PESA Territorial Model

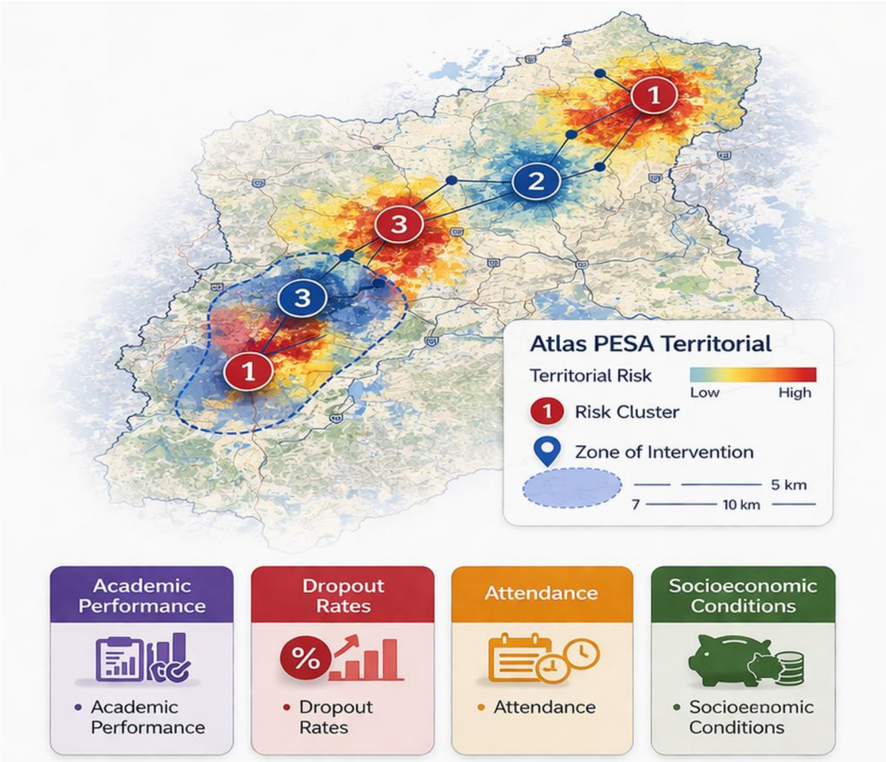


Figure 5 illustrates the Atlas PESA territorial learning analytics model, which integrates institutional educational data with georeferenced analysis in order to identify spatial patterns of student vulnerability. The model visualizes territorial risk through spatial distribution patterns, highlighting areas in which students may face higher probabilities of academic disengagement or dropout.

Atlas PESA combines multiple data sources—including academic performance, attendance, dropout rates, and socioeconomic indicators—with geographic information such as students' place of residence and mobility patterns. This integration makes it possible to identify territorial inequalities, including accessibility barriers, transportation challenges, and regional socioeconomic conditions that may influence academic trajectories.

By mapping these variables territorially, the model supports the identification of intervention zones and enables institutions to design targeted strategies that take into account both academic and contextual factors. In this way, the territorial dimension expands conventional learning analytics by incorporating the broader social and geographic conditions that shape student persistence.

The analytical results suggest that student risk is not evenly distributed, but tends to concentrate in specific territorial contexts marked by socioeconomic constraints, mobility challenges, or limited access to resources. This pattern reinforces the argument that persistence is not solely an institutional or individual phenomenon, but is also shaped by broader social and geographic conditions.

Accordingly, the inclusion of territorial analytics allows institutions to design more context-sensitive interventions that address not only academic needs, but also structural barriers affecting student participation and continuity. This perspective aligns with emerging discussions on equity and social justice in higher education (Unesco, 2018) and highlights the importance of contextual factors in student success strategies.

Theoretical Advancement: Toward a Systemic Paradigm of Persistence

The analytical results presented in this study contribute to ongoing debates on student persistence by reinforcing the limitations of linear and unidimensional explanatory models. The patterns identified through the proposed framework support the argument that persistence is better understood as a complex and multidimensional process in which outcomes emerge from the interaction of multiple dimensions.

Rather than claiming definitive empirical confirmation, the study offers analytical support for MIPESA as a systemic and integrationist theoretical framework. In addition, the operationalization of the model through IPE-PESA and API illustrates how theoretical constructs can be translated into actionable analytical and institutional structures.

This articulation of theory, analytics, and institutional practice represents an important contribution to the field by helping to bridge the gap between conceptual explanation and institutional application. It also positions student persistence within a broader paradigm of institutional intelligence, in which data-informed insights support strategic decision-making in higher education.

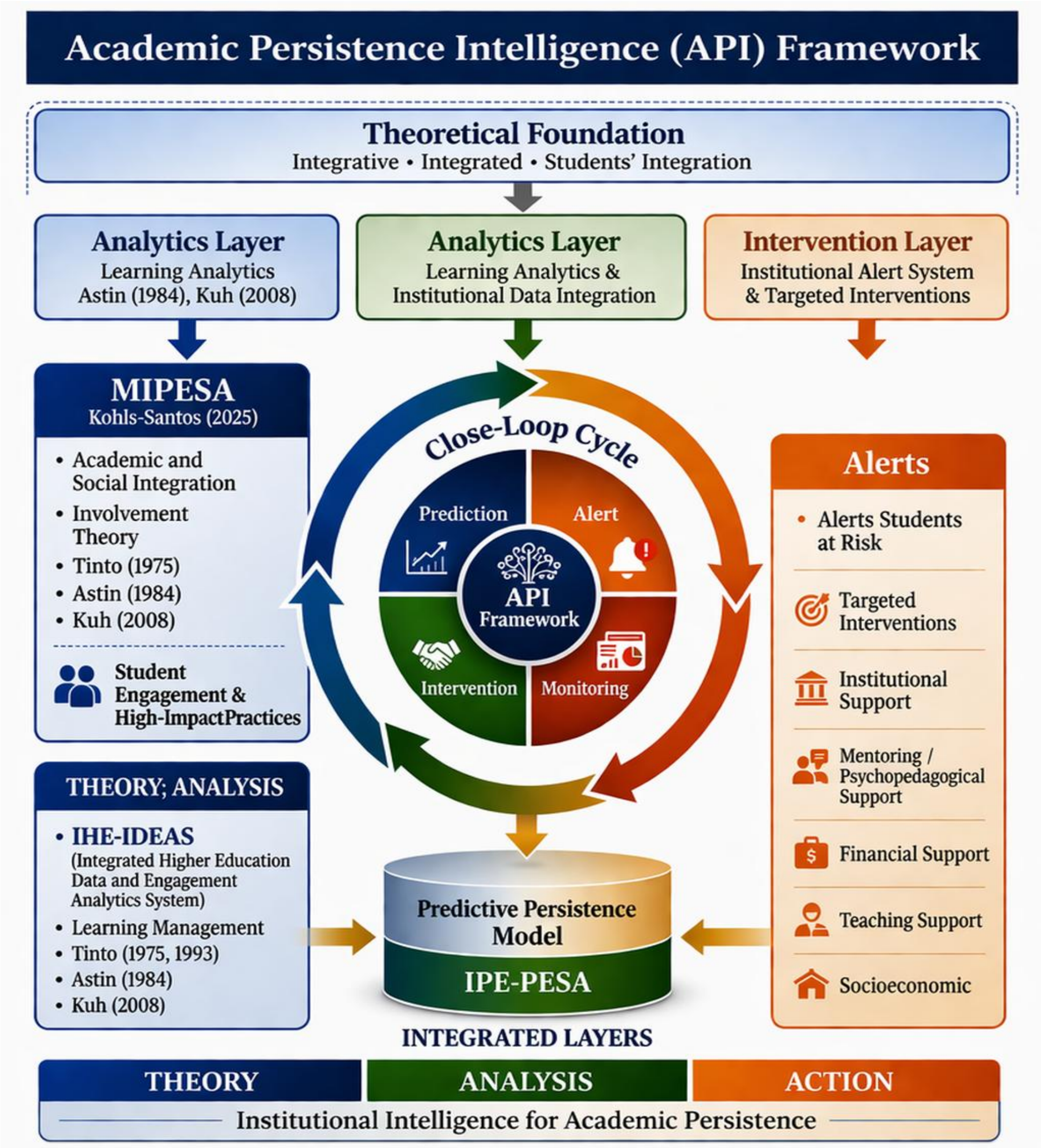
Implications for Institutional Practice

From an institutional perspective, the analytical results suggest that effective strategies for promoting student persistence should move beyond isolated interventions and toward integrated and systemic approaches. The use of analytical models such as IPE-PESA may enable institutions to:

- identify students exposed to greater levels of academic risk with greater precision;
- prioritize interventions according to differentiated risk levels;
- monitor the effectiveness of support strategies over time;
- continuously refine policies and practices aimed at student persistence.

Moreover, the concept of Academic Persistence Intelligence highlights the need for institutional structures capable of integrating data, theory, and action. This requires not only technological infrastructure but also organizational alignment among academic units, student support services, and institutional leadership.

Figure 6. Academic Persistence Intelligence (API) Framework



Source: Author's own elaboration, based on the MIPESA model (Kohls-Santos, 2025).

Figure 6 presents the Academic Persistence Intelligence (API) Framework, an integrative model that connects theory, analytics, and institutional action in support of student persistence and academic success. The framework is grounded in the theoretical understanding of persistence developed through MIPESA and operationalized through the PESA system, which applies learning analytics to institutional data.

Within this architecture, the Student Persistence Index (IPE-PESA) functions as the central analytical component, translating institutional data into multidimensional risk indicators. Atlas PESA adds a territorial layer to the framework by identifying spatial patterns of vulnerability and supporting geographically sensitive institutional responses.

The integration of these components enables the development of alert systems, intervention monitoring mechanisms, and policy support tools. By articulating theoretical constructs, analytical models, and practical applications, the API Framework offers a comprehensive approach to academic intelligence and supports predictive, proactive, and context-sensitive institutional action aimed at strengthening student persistence.

Conclusion, Implications and Future Research

This article has argued that student persistence should not be understood merely as an individual outcome, but as the result of complex and interdependent systems that can be analytically modeled and institutionally supported. By articulating the MIPESA model, the Student Persistence Index (IPE-PESA), the concept of Academic Persistence Intelligence (API), and the territorial dimension represented by Atlas PESA, the study advances an integrative framework for understanding and operationalizing student persistence in contemporary higher education.

The main contribution of the article lies in connecting educational theory, learning analytics, and institutional decision-making within a single analytical architecture. In doing so, it moves beyond explanatory models that remain primarily descriptive and beyond analytics approaches that remain predominantly technical. The proposed framework instead positions student persistence as a dimension of institutional intelligence, capable of supporting proactive, evidence-informed, and context-sensitive action.

From an institutional perspective, the study suggests that persistence strategies are likely to be more effective when they are embedded in systemic structures that connect prediction, intervention, monitoring, and evaluation. This implies that higher education institutions should not rely solely on isolated support measures, but should develop coordinated arrangements involving academic management, teaching practices, student support services, and institutional data systems. The framework proposed here may therefore support the design of more integrated persistence policies and strengthen institutional capacity for strategic action.

At the same time, the study has important limitations. The analytical validation presented in this article is based on a model-development and simulation-oriented strategy, rather than on large-scale empirical implementation across multiple institutional settings. For this reason, the article should be understood as offering a theoretically grounded and analytically structured framework whose broader empirical validation remains to be developed.

Future research may advance this agenda in at least four directions. First, the model should be empirically tested with real-world institutional datasets in order to assess its predictive performance and practical applicability. Second, comparative studies across institutions and national contexts may help evaluate the adaptability of the framework to different higher education systems. Third, further investigation is needed into the ethical, political, and governance implications of predictive systems focused on student persistence. Fourth, future studies may deepen the territorial dimension of learning analytics by examining how spatial inequalities interact with academic and institutional factors in shaping student trajectories.

Taken together, these developments may contribute to a new research agenda in higher education, one in which student persistence is understood not only as a pedagogical or institutional concern, but also as a strategic field of academic intelligence oriented toward equity, sustainability, and student success.

AI Use Statement

ChatGPT (OpenAI, GPT-5.4 Thinking) was used for language refinement and editorial revision of the manuscript. The tool was used exclusively to improve clarity, grammar, and structure. All conceptual decisions, interpretations, and final revisions were made and verified by the author.

Disclosure Statement

The author reports no conflict of interest.

Data Availability Statement

The data supporting the findings of this study are included within the manuscript.

Os dados que apoiam as conclusões deste estudo estão disponíveis mediante solicitação razoável ao autor correspondente.

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