



THE DIGITAL ECONOMY AND THE ENGAGEMENT CRISIS: UNIVERSITY DROPOUT IN THE ERA OF DIGITAL TRANSFORMATION

Monika Paula Górowska^{1*} , Joanna Felczak² , Michał Kapala¹

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¹ Nowy Sącz School of Business National
Louis University, Nowy Sącz, Poland

² Warsaw School of Economics (SGH),
Warsaw, Poland

*Corresponding Author:
Monika Paula Górowska

Email:
mgorowska@wsb-nlu.edu.pl

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ABSTRACT

This article examines the complexity of university dropout in the context of digital transformation and growing labor market uncertainty associated with the rapid development of artificial intelligence. Designed as a conceptual and methodological contribution rather than an empirical study, it evaluates the diagnostic potential of institutional information systems, using the CloudA platform as an illustrative case, and proposes methodological improvements intended to support student retention. The first part reviews established theoretical models of student dropout and considers their relevance to the contemporary use of learning analytics. The central contribution of the article is an original classification of direct indicators available within institutional information systems, organized into academic, behavioral, and institutional dimensions. The paper also proposes composite indicators, including the Moment of Trouble and Financial Risk scales, which are intended to transform transactional data into measurable early warning signals. These indicators remain conceptual and require future empirical validation. The discussion identifies important limitations in the capacity of institutional information systems to capture psychosocial factors. It therefore emphasizes the need to combine data-based analysis with human centered institutional support. The effectiveness of dropout prevention is likely to depend not only on the accuracy of analytical indicators, but also on the speed, appropriateness, and quality of the institutional response to the risks identified.

Keywords: *university dropout, student attrition, learning analytics, early warning systems, higher education, Cloud system, conceptual framework*

1. INTRODUCTION

University dropout has become one of the most significant challenges confronting contemporary higher education. Although the phenomenon itself is not new, its present dynamics are increasingly shaped by the digital transformation of the economy and by uncertainty surrounding the future of work. As Parra Sánchez et al. (2023) observe, student dropout has developed into a global problem whose consequences extend beyond universities and affect economic development, social mobility, and the broader structure of society.

Available evidence illustrates the scale and diversity of the problem. OECD data indicate sub-

stantial differences among countries. Dropout rates in Denmark and Japan remain close to 20 percent, while in the United States and New Zealand they approach 50 percent. Europe also presents a highly uneven picture. According to **Eurostat data published in 2025**, approximately one in seven young Europeans had interrupted their education, while the proportion was considerably higher in some countries, including the Netherlands, where it reached 32.2 percent. Financial difficulties are often assumed to be the principal reason for leaving higher education. However, students also frequently identify dissatisfaction with the curriculum, academic difficulty, and a lack of alignment between study programs and their expectations. These findings suggest that the educational offer of universities may increasingly diverge from the needs and aspirations of young people, particularly in a labor market shaped by digitalization and rapid technological change.

This misalignment is accompanied by a broader decline in confidence in the value of higher education. **The EDUCAUSE Horizon Report (2024)** suggests that universities face growing pressure to demonstrate their social and economic relevance. Similar concerns are reflected in a Gallup study from 2023, which reported that confidence in higher education in the United States had fallen to 36 percent, representing a decline of approximately 20 percentage points over a decade. The traditional perception of a university degree as a secure route to professional success is therefore weakening.

The economic returns to higher education nevertheless remain substantial. Data reported by **Gallup and the Lumina Foundation indicate that graduates in 2024** earned considerably more than individuals with only a secondary school qualification, with a reported median income of USD 132,700. Despite this earnings advantage, the proportion of respondents who considered a university degree essential reportedly declined from 75 percent to 35 percent. This contrast suggests that the objective economic benefits of higher education no longer translate automatically into confidence in its necessity or relevance.

Members of Generation Z appear particularly exposed to these uncertainties. According to **Indeed (2025)**, almost half of young people fear that the knowledge and skills acquired during their studies may become obsolete before graduation. This concern presents a serious challenge for universities because artificial intelligence is increasingly capable of performing tasks traditionally associated with entry level employment. **Brynjolfsson et al. (2025)** similarly identify employment declines among workers aged between 22 and 25 in occupations more exposed to artificial intelligence.

At the same time, student attitudes toward artificial intelligence are becoming more cautious. **Brenan (2026)** reports that the share of young people who believed that artificial intelligence supported their learning fell to 46 percent within one year. This decline suggests that students may simultaneously recognize the importance of artificial intelligence and remain uncertain about its educational value and its consequences for future employment.

Taken together, these developments indicate that university dropout in the age of artificial intelligence is a multidimensional phenomenon. It is shaped by concerns about automation, uncertainty regarding employment, perceptions of curricular inadequacy, academic difficulty, and declining confidence in the value of a degree. A systematic understanding of these mechanisms requires a return to the principal theoretical explanations of student persistence and withdrawal.

Artificial intelligence is treated in this article primarily as a contextual and motivational factor that reshapes labor market expectations, perceptions of curricular relevance, and student confidence. It is not used as an analytical technique within the proposed framework. The framework instead relies on established learning analytics indicators derived from institutional information systems. The following section therefore reviews the theoretical foundations of

university dropout and evaluates their relevance to the contemporary digital environment.

2. LITERATURE REVIEW

2.1. FROM SOCIOLOGY TO DIGITAL DATA: THE EVOLUTION OF ATTRITION THEORY

Systematic research on student retention emerged during the late 1960s and 1970s, when dropout began to be understood not merely as an individual failure but as the outcome of interactions between students and educational institutions (Valencia Arias et al., 2026). Early sociological models established the theoretical foundations of this field.

Spady (1970), drawing on Durkheim's theory of suicide, conceptualized dropout as the gradual consequence of insufficient integration into the academic and social environment rather than as a sudden decision (Valencia Arias et al., 2026). This perspective was further developed by Tinto (1975, 1993), whose Institutional Departure Model remains one of the most influential frameworks in the literature, accounting for 36.8 percent of identified applications. According to Tinto, persistence depends largely on academic and social integration. Students who develop stronger relationships with peers, faculty members, and the wider university community are more likely to remain enrolled and complete their studies (González Morales et al., 2025).

Tinto's model, however, has been criticized for insufficiently accounting for students whose participation in university life is constrained by employment, family responsibilities, or other external obligations. Bean (1980, 1982) addressed this limitation by applying an organizational turnover perspective to student attrition. In this framework, the decision to leave university resembles an employee's decision to leave an organization and is influenced by external conditions, including financial pressure, professional commitments, family circumstances, and emotional responses to the institution (Valencia Arias et al., 2026). Bean and Metzner (1985) later extended this reasoning to nontraditional students, for whom environmental factors outside the institution may be more important than campus integration.

Astin's (1984) theory of Student Involvement offered a related but distinct perspective. Rather than focusing primarily on institutional attachment, Astin argued that educational outcomes depend on the amount of physical and psychological energy students invest in academic and extracurricular activities. From this perspective, persistence is associated with the intensity and continuity of student participation in the university experience.

The expansion of online and blended learning challenged assumptions embedded in traditional campus-based models. In digital environments, social integration is no longer defined exclusively through physical interaction. Rovai (2003) therefore emphasized the importance of a sense of community in online education, arguing that perceived connectedness and belonging can reduce isolation and strengthen persistence.

The development of learning analytics represents a further stage in the evolution of attrition research. Earlier models relied heavily on surveys and self-reported attitudes, whereas contemporary approaches increasingly examine behavioral data generated by institutional information systems. Digital traces such as login frequency, time spent on learning activities, assignment submission patterns, click activity, and participation in online discussions are used as observable indicators of engagement and involvement (Kuh, 2007; Siemens, 2012; Gašević et al., 2016). These data enable institutions to monitor changes in student behavior over time and potentially identify emerging risks before formal withdrawal occurs.

Learning analytics therefore translates abstract concepts such as involvement, integration, and engagement into measurable behavioral indicators. However, this transformation remains con-

ceptually incomplete. A digital trace is not equivalent to the psychological or social construct it is intended to represent. Frequent logins may indicate engagement, but they may also reflect confusion, administrative requirements, or inefficient study behavior. Similarly, limited online activity does not necessarily demonstrate weak commitment, particularly when students rely on offline resources or combine study with employment.

The classical theories are therefore not fully reconcilable. Tinto's (1975, 1993) integration model and Rovai's (2003) sense of community construct treat persistence primarily as a relational process, whereas Bean's (1980, 1982) organizational model emphasizes pressures external to the university. This distinction is particularly important for working, commuting, and nontraditional students, for whom campus integration may be neither feasible nor the principal determinant of persistence (Bean & Metzner, 1985).

Learning analytics inherits rather than resolves this theoretical tension. Behavioral indicators capture what students do within digital systems, but they cannot fully explain why they behave in a particular way or whether their actions reflect motivation, belonging, financial stress, mental health difficulties, or external obligations. Gašević et al. (2015) report that such indicators explain only a limited proportion of variation in academic outcomes, approximately 21 percent. This limitation is therefore not only technical but also conceptual, because behavioral data and theoretical constructs of attrition operate at different levels of analysis.

2. 2. WHY DO STUDENTS LEAVE? A TYPOLOGY OF FACTORS

Student withdrawal rarely results from a single cause. The literature consistently presents dropout as a multidimensional and multilevel process in which academic, economic, psychosocial, and institutional factors interact over time. Recent systematic reviews have identified more than 500 potential determinants of attrition, illustrating both the complexity of the phenomenon and the difficulty of constructing universally applicable predictive models (Quincho Apumayta et al., 2024). For analytical purposes, these determinants can be organized into four broad categories (Valencia Arias et al., 2026).

First, academic factors are among the most consistent predictors of dropout. Low grades, repeated course failure, delayed assignment submission, poor attendance, weak study habits, procrastination, and dissatisfaction with teaching quality can all increase the probability of withdrawal. These factors often reinforce one another. Students who repeatedly experience academic difficulty may lose confidence in their ability to succeed, reduce their engagement, and ultimately decide to leave the institution. This process can create a cumulative cycle in which poor performance weakens motivation and declining motivation further reduces academic achievement (de la Cruz Campos et al., 2023; Núñez Naranjo, 2024). Academic risk is therefore not limited to formal grades. Changes in participation, assessment behavior, study regularity and course progression may provide earlier evidence of difficulty.

Second, economic pressure is an important component of dropout risk, although its effects are rarely isolated from academic and psychosocial conditions. Financial hardship may restrict access to learning resources, increase the need for paid employment, reduce the time available for study, and generate stress that negatively affects concentration and motivation. Valencia Arias et al. (2026) identify financial hardship as a recurrent determinant of attrition and argue that its impact often operates through interactions with psychological and academic difficulties. Institutional support, including scholarships, flexible payment arrangements, emergency assistance, and timely financial counseling, may moderate these effects. Economic risk should therefore be understood as both a direct constraint and an amplifier of other forms of vulnerability.

Third, psychosocial determinants have received increasing attention, particularly since the

COVID 19 pandemic. Motivation, emotional well-being, stress tolerance, social isolation, self-efficacy, and a sense of belonging are consistently associated with persistence. Mental health difficulties can impair academic performance, reduce participation, and weaken students' capacity to respond to setbacks. [Véliz Palomino and Ortega \(2023\)](#) report that mental health concerns and limited resilience have become prominent reasons for withdrawal. [Valencia Arias et al. \(2026\)](#) identify motivation as the most frequently reported predictor of dropout, appearing in 73.7 percent of the reviewed studies, and emphasize its interaction with academic performance and institutional support. Students who feel disconnected from the university community or believe that they lack support may be less likely to seek assistance and more likely to disengage gradually.

Psychosocial risk is particularly difficult to monitor through institutional information systems. Administrative and learning platforms may detect behavioral changes associated with distress, but they cannot directly observe emotional states, family conflict, loneliness, anxiety, or loss of purpose. These factors therefore require human interpretation and complementary support mechanisms.

Fourth, institutional and contextual conditions shape both student experience and the effectiveness of retention interventions. Relevant factors include teaching quality, curriculum organization, administrative clarity, career counseling, accessibility of support services, inclusiveness, digital infrastructure, communication quality, discrimination, and perceived institutional neglect ([Garcés Delgado et al., 2024](#)). [Akpen et al. \(2024\)](#) show that institutional factors can influence psychological distress and persistence through both direct and indirect pathways. Their effects may also differ across student groups, particularly between minority and majority populations. An institution that provides timely information, accessible support, inclusive teaching, and reliable digital services may reduce the impact of academic and personal difficulties. Conversely, fragmented communication, unclear procedures, weak counseling, or inadequate digital infrastructure may intensify existing risks.

These four categories should not be interpreted as independent domains. Academic difficulty may generate psychological distress, financial pressure may reduce participation, institutional neglect may weaken belonging, and low motivation may worsen academic performance. Dropout is therefore best understood as a dynamic process produced by the interaction of multiple risk factors rather than as the outcome of a single identifiable cause.

2. 3. SUMMARY OF THE MOST CONSISTENT PREDICTORS

The strongest evidence concerns academic performance and motivation, which consistently emerge as stable predictors across systematic reviews and structural equation models. Social integration and institutional support also demonstrate robust direct and mediated effects on student persistence ([Valencia Arias et al., 2026](#)). By contrast, economic and institutional factors often operate as moderators or through interactions with psychosocial variables rather than as direct predictors in tested dropout models. Evidence concerning the effect of digital infrastructure on attrition also remains largely indirect, usually operating through student engagement ([Valencia Arias et al., 2026](#)).

From a technological and information systems perspective, the growing dropout crisis requires more than theoretical interpretation. It also demands operational indicators that institutions can monitor in real time. Classical retention theories provide essential conceptual foundations, but they were not designed to use the digital traces generated by students within institutional systems. Contemporary learning analytics therefore seeks to translate established predictors of attrition into observable indicators while recognizing that not all relevant factors can be captured digitally. In this context, the classification proposed by [Jansone et al. \(2026\)](#) is particularly important.

The authors distinguish between measurable factors, such as grades, attendance, and system logins, which institutional systems can monitor automatically and continuously, and nonmeasurable factors, such as motivation and family circumstances, which require direct contact with students or more extensive diagnostic assessment.

The influence of individual factors ultimately depends on the specific characteristics of each institution and student population (Núñez Naranjo, 2024). Rather than seeking a universally applicable solution, this study therefore examines which theoretically established predictors leave observable traces in institutional information systems and can be transformed into digital early warning signals.

3. METHODOLOGY

This paper adopts a conceptual and methodological research design rather than an empirical or statistically validated approach. Its objective is to develop a coherent classification and indicator framework grounded in established attrition theory and the learning analytics literature. The framework is intended to support subsequent empirical testing rather than to validate a model against observed outcome data.

The study proceeds in three stages. First, a narrative synthesis of classical sociological theories of student attrition, including Spady (1970), Tinto (1975, 1993), Bean (1980, 1982), and Astin (1984), together with contemporary learning analytics research, is used to derive a typology of dropout determinants. This stage also distinguishes between factors that can, in principle, be measured through institutional information systems and those that require other forms of assessment (Jansone et al., 2026).

Second, the resulting typology is applied descriptively to a single institutional case, the CloudA information system used at the authors' institution. This analysis identifies and organizes the categories of indicators currently generated by the system.

Third, the study uses this inventory to propose new composite indicators, including Financial Risk, Moment of Trouble, and Intervention Window. These indicators are developed through conceptual design by specifying their input data, aggregation logic, and intended diagnostic value. Their predictive performance is not tested against historical student records at this stage.

Because the case illustration is based on a single institutional information system, the indicators presented in Section 4 should be interpreted as representative examples of each category rather than as an exhaustive inventory of all 45 indicators generated by the system. This limitation, together with the absence of empirical validation, is discussed further in the Limitations section.

Future research should test the proposed framework through retrospective analysis of historical student records, pilot implementation, and predictive modeling. Such research would make it possible to assess the diagnostic and predictive value of the proposed indicators and determine their applicability across different institutional contexts.

4. THE CLOUDA SYSTEM AS A RISK INDICATOR CASE STUDY

The typology discussed above provides a practical analytical framework for evaluating the CloudA system. During routine university operations, the system automatically generates and records 45 indicators. Their principal advantage is their immediate availability, as they do not require additional data collection. These indicators can be organized into seven main categories that collectively provide a digital profile of the student.

(1) Pre entry Attributes:

Each student record begins with demographic and admission related information, including age, gender, citizenship, and mode of admission. From the perspective of **Tinto's theory (1975, 1993)**, these variables represent pre entry attributes, namely the characteristics students bring with them and which influence their initial capacity to integrate into the institution. **As González Morales et al. (2025)** observe, dropout often develops from conditions associated with prior academic preparation and family background. Particular attention should be paid to nontraditional students, including older students, employed students, and those with family responsibilities. For these groups, external environmental pressures may have a stronger effect on persistence and may place them at greater risk of withdrawal (**Valencia Arias et al., 2026**).

(2) Academic Performance:

This is the largest category, comprising 12 indicators. It includes grade point averages, ratios of completed ECTS credits, the number of examination retakes, repeated semesters, and the timing of the first failed examination period. Low academic efficiency represents an important warning signal because, when it is not identified early, it may contribute to gradual disengagement and eventual withdrawal (**Núñez Naranjo, 2024**). The literature suggests that critical events, such as the first failed course or the need to repeat a subject, may represent turning points in a student's academic trajectory, particularly during the first two years of study (**Quincho Apumayta et al., 2024**).

(3) Behavioral Engagement:

Indicators of activity within the CloudA system, including login frequency, assignment submission, and attendance, form the analytical core of the system. These variables provide a contemporary operationalization of **Astin's (1984)** concept of physical and psychological energy invested in education. Behavioral indicators may reveal emerging difficulties before they become visible in formal academic records. Log data can therefore provide valuable evidence of changes in engagement, although such data must still be interpreted cautiously because observed activity does not necessarily correspond directly to motivation or commitment (**Gašević et al., 2016**).

(4) Financial Situation:

Indicators such as delayed tuition payments and the receipt of social scholarships provide indirect but useful information about students' socioeconomic circumstances. Financial difficulties may increase the risk of dropout by creating stress, limiting study time, or reducing access to educational resources (**Núñez Naranjo, 2024**). However, the system contains an important asymmetry. It identifies students who have formally applied for financial support, but students experiencing similar hardship who have not requested assistance may remain invisible until payment arrears or other difficulties appear.

(5) Critical Events:

The system also records discrete events, including dean's leave, reenrollment, changes in the field of study, and changes in the mode of study. It is particularly important to distinguish between administrative dismissal and voluntary withdrawal. This distinction reflects **Tinto's (1975)** differentiation between forced and voluntary departure, because the two forms of withdrawal arise from different circumstances and require different institutional responses.

(6) Institutional Context

This category includes indicators relating to the educational environment, such as group size, ECTS workload, and course difficulty. As Jansone et al. (2026) emphasize, the quality of instruction and relationships within the institution can significantly affect student persistence. The course difficulty indicator is especially valuable because it helps distinguish between difficulties specific to an individual student and challenges experienced by a broader group of students enrolled in the same course.

(7) Dropout Calendar

The semester and month in which withdrawal occurs are primarily useful for retrospective rather than predictive analysis. Identifying periods of increased attrition within the academic calendar can help institutions allocate counseling, academic support, and financial assistance more effectively during periods when students are most vulnerable (Quincho Apumayta et al., 2024).

(8) Evaluation of the CloudA System's Potential

The analysis of the 45 indicators suggests that the CloudA system provides substantial coverage of four major risk dimensions: academic, economic, behavioral, and institutional. One of its principal strengths is access to temporal data, which enables the institution to observe changes and patterns over time rather than relying only on isolated data points. However, the psychosocial dimension remains a significant blind spot. Factors such as motivation, anxiety, family conflict, loneliness, and a sense of belonging cannot be captured reliably without additional diagnostic instruments and direct interaction with students.

5. RECOMMENDATIONS FOR EXPANDING THE CLOUDA SYSTEM

The CloudA system contains a substantial volume of underused data that could be transformed into more meaningful indicators by connecting individual observations into a coherent account of each student's academic situation. The proposed improvements are organized into three modules, each addressing a different category of risk.

Module I

Detecting Quiet Signals. This module would function as an early warning mechanism focused on changes that occur between formal examination periods. In many cases, withdrawal is not caused by a lack of academic ability but by a sudden financial, personal, or psychological crisis that leads the student to disengage gradually. Without additional analytical indicators, the system may record only an overdue tuition payment. By combining this information with changes in attendance, login activity, assignment submission, and academic performance, the institution could interpret late payment not merely as a financial obligation but as a possible signal of broader vulnerability. This would make it possible to offer emergency financial assistance, counseling, or other forms of support before the student reaches the stage of formal dismissal.

Table 1. Composite Indicators for Detecting Quiet Signals

Indicator Name	Input Data (What are we connecting?)	Algorithm / Rule	Diagnostic Value
Financial Risk (FR)	Arrears + Scholarships + Emergency Grants	0–4 Scale (cumulative events)	Detects student impoverishment before they withdraw due to lack of funds.
Moment of Trouble (MOT)	Dates of first failures and financial warnings	Min(event_date)	Identifies „Ground Zero” – the onset of the crisis.
Intervention Window (IW)	Dismissal date minus MOT	Time difference (weeks)	Measures how much time the university had to react before it was too late.

Source: Authors' own elaboration

Module II

Recognizing Entry Barriers. In this module, we connect the recruitment database with market data to understand whether a student's individual difficulties stem from a lack of knowledge, "culture shock," or other factors beyond their control.

Table 2. Composite Indicators for Recognizing Entry Barriers

Indicator Name	Input Data (What are we connecting?)	Algorithm / Rule	Diagnostic Value
Geocoding	Student's address + Central Statistical Office database (TERYT)	Settlement type (village/city)	Identifies first-generation students at risk of social isolation.
Maturity Exam Significance	High school exit exam results + Current grades	Mapping of entry results	Allows for the recommendation of remedial courses as early as October.
Negative Grade Concentration	Course ID + Instructor ID	% of failures per instructor	Distinguishes student-specific issues from problems with instructional quality.

Source: Authors' own elaboration

This module performs an important equity function. If a student comes from a rural area and enters university with a low score on the secondary school mathematics examination, the system can identify this risk from the beginning through admission and exit examination data. Rather than waiting for the student to fail during the examination period, the institution could proactively invite them to attend supplementary workshops or targeted academic support sessions. Conversely, data on the concentration of failing grades can help protect students from being treated as isolated cases. If a large proportion of a group fails a particular course or assessment, the system may indicate that the difficulty is not confined to individual students but may also be related to course design, assessment structure, or instructional conditions.

These indicators nevertheless require cautious interpretation. Geocoding based inferences may produce an ecological fallacy because settlement type is only a broad proxy for an individual student's socioeconomic circumstances. Treating area level characteristics as if they were direct attributes of a particular student may therefore lead to misclassification. Similarly, a high concentration of failing grades should not be interpreted automatically as evidence of weak teaching quality or inappropriate curriculum design. Alternative explanations may include an unusually underprepared cohort, a small sample, an exceptionally demanding assessment, or a recurring course design problem affecting several instructors. This indicator should therefore

be used as a trigger for further qualitative and institutional review rather than as a direct measure of instructional quality.

Module III

Subjective Perspective. This module extends the system beyond the observation of student behavior by recording whether students seek assistance and, where possible, the reasons underlying their difficulties or eventual withdrawal. Its purpose is to complement transactional and administrative data with information that institutional systems cannot infer reliably from digital traces alone.

Table 3. Composite Indicators for Capturing the Subjective Perspective

Indicator Name	Input Data (What are we connecting?)	Algorithm / Rule	Diagnostic Value
Support Utilization	Visit logs (psychologist/tutor)	Binary variable (YES/NO)	Demonstrates student resourcefulness and the effectiveness of support processes.
Thesis Progress	Seminar start date + duration	Semesters beyond the norm	Identifies students who have „stalled” at the final hurdle.
EXIT Survey	Survey after dismissal/ withdrawal	Automatic trigger (email)	Unveils underlying reasons (stress, relocation) that are absent from system logs.

Source: Authors' own elaboration

Seeking help is itself an important indicator that a student is experiencing difficulties and is actively attempting to overcome them. The EXIT Survey, by contrast, represents the institution's final opportunity to understand the reasons for withdrawal. For example, if a student leaves because they have moved to another city, only direct feedback may reveal that an offer to transfer to a remote mode of study could have enabled them to continue their education.

The division into three modules is a deliberate methodological choice intended to provide a multidimensional understanding of dropout. Module I functions as an early warning mechanism by identifying dynamic changes in a student's financial, academic, and temporal circumstances and detecting emerging difficulties before they result in withdrawal. Module II introduces contextual awareness by combining academic data with socioeconomic and institutional information, thereby helping to distinguish individual difficulties from broader structural barriers. Module III provides a feedback loop by recording support seeking behavior, institutional interventions, and the student's own account of the reasons for departure.

Integrating these rules into the CloudA system would transform it from a passive administrative archive into a more responsive decision support tool. Rather than treating digital traces as isolated records, the system would connect them into a broader interpretation of the student's changing academic and personal trajectory. However, such interpretation should support rather than replace professional judgment, direct communication, and human centered institutional assistance.

6. DISCUSSION

6.1. THE DIAGNOSTIC POTENTIAL OF THE CLOUDA SYSTEM: FROM DESCRIPTION TO PREDICTION

The analysis of indicators available within the CloudA system suggests that the university possesses considerable analytical potential that remains only partially utilized. The identified indicators, including pre entry characteristics, academic performance data, financial records,

and behavioral logs, provide the basic components of what the literature defines as an Early Warning System.

A central insight of the analysis is that it supports the process based understanding of attrition proposed by Tinto (1975, 1993). Student withdrawal is rarely a single or sudden event. It more often develops through a gradual process of disengagement from academic and institutional life. CloudA records several elements of this process in real time, including declining login activity, reduced attendance, delayed assignment submission, deteriorating academic performance, and payment arrears. However, the diagnostic value of these data remains limited when indicators are interpreted separately and without defined aggregation rules. The proposed Moment of Trouble indicator and the monitoring of risk periods seek to operationalize the intervention window during which institutional support may still prevent withdrawal. Their introduction would enable a shift from passive event recording toward active monitoring of the attrition process.

The proposed composite indicators represent the dormant analytical capacity of the system. Indicators such as Negative Grade Concentration and Financial Risk do not necessarily require the collection of new data. Instead, they add an interpretive layer to information that the institution already possesses. From the perspective of learning analytics, the principal challenge is therefore not the volume of available data but the ability to identify meaningful relationships and patterns within them (Siemens & Baker, 2012).

Relational indicators that connect admission results with subsequent academic performance may be especially valuable. They could help institutions identify groups requiring additional support from the beginning of their studies. However, characteristics such as first generation status should be included only where they are directly and reliably recorded rather than inferred from indirect proxies. Tools such as the exit survey also provide an essential feedback mechanism by capturing reasons for withdrawal, including emotional distress, motivational decline, relocation, family circumstances, or dissatisfaction with the study program, that remain largely invisible in transactional data (Gallup & Lumina Foundation, 2024).

A major structural limitation of an exclusively system based approach is the limited visibility of psychosocial factors. Motivation, belonging, resilience, and the quality of interpersonal relationships are central to student persistence (Astin, 1984; Rovai, 2003), yet they do not leave direct and unambiguous traces in institutional logs. Behavioral data may show what a student is doing, but they cannot reliably explain why the student behaves in a particular way. Reduced system activity, for example, may reflect disengagement, illness, employment obligations, family pressures, technical difficulties, or the use of learning resources outside the institutional platform.

System analytics should therefore be treated as a mechanism for screening and prioritization rather than as the sole basis for diagnosis. The system can identify patterns that may indicate elevated risk, but subsequent interpretation and intervention must remain centered on the individual student. Psychological and advisory support is not an optional addition to the analytical process. It is necessary for understanding the external circumstances that may shape student behavior, including employment, financial hardship, caring responsibilities, and family conditions. For nontraditional students, such external factors may be more influential than internal university experiences (Bean & Metzner, 1985).

Based on the conceptual analysis, four recommendations are proposed for institutional policy:

1. **Operationalization of existing data:** Type I indicators should be implemented as a relatively low cost means of improving the diagnostic capacity of the existing system.
2. **Modular integration:** Recruitment, financial, academic, and behavioral data should be connected within a shared analytical environment to reduce fragmentation across

institutional information systems.

3. **Standardization of the exit survey:** A consistent exit survey should be introduced to collect information on students' stated reasons for withdrawal and to support the improvement of programs and institutional services.
4. **Screening based psychosocial monitoring:** Brief and ethically designed survey instruments should be administered at selected points in the academic year to identify motivational, emotional, and social difficulties before they become visible through behavioral decline.

The implementation of this framework also involves practical challenges beyond conceptual design. From a technical perspective, data currently stored in separate recruitment, financial, and academic modules would need to be integrated into a common analytical layer. This may require investment in interoperability, data quality, access controls, and institutional infrastructure. From an operational perspective, advisors, tutors, and administrative staff would require training to interpret composite indicators appropriately and to convert a risk signal into a timely and nonstigmatizing response.

Organizational arrangements are equally important. Cross departmental data sharing may be constrained by existing governance structures, unclear responsibilities, and legal or ethical concerns. Pilot implementation may therefore require formal data sharing rules, clearly assigned institutional responsibility, and a designated data stewardship function. Safeguards should also ensure that indicators are used to provide support rather than to label, penalize, or exclude students.

The CloudA system offers an objective and scalable foundation for monitoring student trajectories. Its principal limitation is that the decision to leave university often develops within a subjective and relational sphere that institutional data cannot fully capture. An effective approach to dropout prevention should therefore combine behavioral analytics with a culture of timely and accessible support. Within such a model, the system identifies patterns requiring attention, while qualified staff interpret those patterns and determine the appropriate intervention.

The effectiveness of an Early Warning System is therefore likely to depend not only on the accuracy of its indicators but also on the speed, appropriateness, and quality of the institutional response to the signal generated (Vasconcelos et al., 2023). This proposition, together with the composite indicators introduced in Section 5, remains a hypothesis requiring empirical validation rather than a demonstrated result of the present study. A responsive university is not one that merely collects more data, but one that uses available information responsibly to understand and support the changing needs of its students.

7. ETHICAL CONSIDERATIONS

Here is the revised version, preserving the existing headings and structure without adding new subheadings:

The indicators discussed throughout this paper rely on institutional data that are inherently sensitive. Academic records, financial information, and behavioral logs may reveal substantial details about a student's personal and socioeconomic circumstances. Their use for early warning purposes therefore raises important ethical concerns that must be acknowledged within the proposed conceptual framework, even though the present study does not involve the implementation of an operational system.

Privacy and data protection represent the first major concern. Because the institutions considered in this study operate within the European Union, any future implementation of the proposed indicators would need to comply with the General Data Protection Regulation. This

would require adherence to principles such as purpose limitation, data minimization, proportionality, secure processing, and the establishment of a clear legal basis for using institutional data for student retention and support rather than solely for routine administrative purposes.

Transparency is equally important. Students should be informed that their institutional data may be used to generate risk indicators and should receive a general explanation of the types of data involved, the purposes for which they are processed, and the manner in which risk classifications may influence institutional support. They should also have access to a clear mechanism through which they can question, correct, or contest a classification. These safeguards are consistent with broader principles of accountability and algorithmic transparency in educational settings.

Algorithmic bias constitutes an additional risk, particularly for indicators based on indirect proxies. As discussed in the Limitations section, variables such as geocoded address data and concentrations of failing grades may systematically misclassify or disadvantage particular groups if interpreted without adequate contextual review. Any future operational use of such indicators should therefore be preceded by an assessment of measurement validity and fairness and should include regular monitoring for unequal effects across student groups.

Finally, institutional data governance must be defined before any of the indicators proposed in Section 5 are implemented. Policies should specify who is authorized to access individual risk assessments, for what purposes they may be used, how long the underlying data and generated scores are retained, and how they are securely stored. Clear accountability should also be assigned for reviewing risk classifications, managing student inquiries, and ensuring that the system is used to provide support rather than to penalize or stigmatize students.

8. LIMITATIONS

This study has several limitations that should be considered when interpreting its contribution. First, and most importantly, the study is conceptual. The proposed composite indicators, including Financial Risk, Moment of Trouble, and Intervention Window, have not been empirically validated against historical student outcomes. Their inclusion should therefore not be interpreted as evidence of predictive accuracy, diagnostic effectiveness, or causal validity.

Second, the case illustration is based on a single institutional information system, CloudA. The seven indicator categories discussed in Section 4 are presented as representative examples rather than as a complete inventory of all 45 indicators generated by the system. Both the proposed categorization and its applicability to other institutional information systems require further investigation.

Third, several indicators rely on indirect proxies. Geocoded address data are used as a possible indicator of socioeconomic vulnerability, while the concentration of failing grades is treated as a potential signal of problems associated with course design, assessment, or instructional conditions. These proxies are vulnerable to ecological fallacy, measurement error, and contextual misinterpretation and should not be treated as direct measures of the underlying constructs.

Fourth, the framework remains structurally limited in its ability to capture the psychosocial dimensions of student attrition. Motivation, sense of belonging, emotional well-being, social integration, and the quality of interpersonal relationships are repeatedly identified in the literature as important influences on persistence, yet they cannot be observed directly through administrative and behavioral records. The exit survey proposed in Module III provides only a partial response because it primarily captures the student's perspective after the decision to withdraw has already been made.

Finally, the generalizability of the framework beyond the Polish higher education context in which CloudA operates has not been assessed. Differences in institutional structures, funding systems, legal requirements, student populations, educational cultures, and data governance

practices may limit the extent to which the proposed indicators can be transferred directly to other national or institutional settings.

9. CONCLUSION

This paper proposes a conceptual framework for reinterpreting data already collected by institutional information systems, illustrated through the case of CloudA, as a potential foundation for the early identification of dropout risk. By classifying existing data into distinct indicator categories and introducing composite measures such as Financial Risk, Moment of Trouble, and Intervention Window, the framework demonstrates how routinely generated information could, in principle, support earlier and more targeted institutional responses.

The analysis suggests that the principal value of institutional data does not lie only in the number of variables collected but in the ability to connect them across time and institutional domains. Academic, financial, behavioral, and administrative records may collectively reveal emerging patterns of disengagement that would remain less visible if each indicator were considered in isolation. The proposed framework therefore seeks to transform the information system from a passive repository of records into a more responsive decision support mechanism.

At the same time, the paper argues that such a system should function primarily as a screening and prioritization tool rather than as a substitute for professional judgment. Institutional data may help identify students who require attention, but they cannot fully explain the personal, emotional, social, or family circumstances underlying observed behavior. The psychosocial dimensions of the decision to withdraw remain largely beyond the direct reach of institutional information systems and require communication with students and interpretation by qualified staff.

The claims advanced in this paper should therefore be understood as a research agenda rather than as established empirical findings. The diagnostic value of the proposed indicators, their predictive performance, their applicability beyond a single institution, and the adequacy of the associated ethical and governance safeguards all require further investigation. Retrospective validation, pilot implementation, fairness assessment, and comparative institutional research are necessary before operational conclusions can be drawn.

An effective Early Warning System should ultimately combine responsible data analysis with timely, proportionate, and person-centered support. Technology can help institutions recognize emerging risk, but its value will depend on whether the resulting signals lead to appropriate human intervention. The contribution of the proposed framework lies in providing a structured basis for testing how this relationship between institutional data and human response might be developed in future research.

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