COMPARING UDL AND RADITIONAL E-LEARNING COURSES: LEVERAGING EDUCATIONAL DATA MINING TO ENHANCE SELF-REGULATED LEARNING AND MOTIVATION

CONFRONTO TRA CORSI E-LEARNING IN MODALITÀ UDL E TRADIZIONALE: VALORIZZARE L'EDUCATIONAL DATA MINING PER POTENZIARE L'AUTOREGOLAZIONE DELL'APPRENDIMENTO E LA MOTIVAZIONE

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ABSTRACT

This work is presented as a position paper aimed at introducing an analytical framework accompanied by a project proposal comparing two university courses: one implemented according to the principles of Universal Design for Learning (UDL) and the other using a traditional approach, utilizing Educational Data Mining (EDM) to analyze data indicative of learning processes. The objective is to assess how the UDL approach influences Self-Regulated Learning (SRL) processes and student motivation. The project aims to structure a computational theoretical framework encompassing variables such as engagement, perceived self-efficacy, and academic outcomes, to identify the advantages of UDL implementation in enhancing self-regulation and learning motivation. This approach allows for evaluating the effectiveness of the two educational strategies, providing concrete data to optimize the learning experience and improve academic results.

Il lavoro in oggetto si pone come un position paper finalizzato a presentare un framework analitico corredato da una proposta progettuale di confronto tra due corsi di studio universitari, uno implementato secondo i principi dell'Universal Design for Learning (UDL) e l'altro in modalità tradizionale, utilizzando l'Educational Data Mining per analizzare i dati indicativi dei processi di apprendimento. L'obiettivo è valutare come l'approccio UDL influenzi i processi di Self-Regulated Learning (SRL) e la motivazione all'apprendimento. Il progetto ha come finalità la strutturazione di un framework teorico di natura computazionale che comprenda variabili come l'engagement, l'autoefficacia percepita e i risultati accademici, al fine di identificare i vantaggi dell'implementazione UDL nel migliorare l'autoregolazione dell'apprendimento e la motivazione degli studenti. Questo approccio consente di valutare l'efficacia delle due strategie educative, fornendo dati concreti per ottimizzare l'esperienza di apprendimento e migliorare i risultati accademici.

KEYWORDS

Universal Design for Learning, Self-Regulated Learning, Learning Motivation, Educational Data Mining, Self-Efficacy
Universal Design for Learning, Self-Regulated Learning, Motivazione all'apprendimento, Educational Data Mining, Autoefficacia

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Introduction

The implementation of Universal Design for Learning (UDL) represents an innovative strategy to promote inclusive, flexible, and accessible educational environments, aligned with the needs of an increasingly diverse student population (Rose & Gravel, 2010). This approach, based on the principles of multiple means of representation, flexible action/expression, and active engagement, aims to reduce educational barriers through curricular design that fosters Self-Regulated Learning (SRL) and motivation (Al-Azawei et al., 2017; Kumar & Wideman, 2014). Despite its potential advantages, challenges remain concerning the empirical assessment of UDL's effectiveness, especially in higher education contexts where student heterogeneity demands personalized solutions (Sáiz-Manzanares et al., 2020; Widodo, 2023).

Recent studies have highlighted how Educational Data Mining (EDM) offers advanced tools to analyze behavioral, cognitive, and emotional data, allowing the identification of patterns related to engagement, perceived self-efficacy, and academic outcomes (Boulahmel et al., 2025; Saint et al., 2022). The integration of mixed methodologies (quantitative and qualitative) with machine learning techniques, such as clustering and predictive models, has enabled the mapping of interactions between instructional strategies and SRL processes (Sáiz-Manzanares et al., 2020; Al-Azawei et al., 2017). However, the literature points to a lack of systematic research comparing the impact of UDL with traditional approaches using multimodal data to assess both learning outcomes and the underlying mechanisms of self-regulation (Heikkinen et al., 2023; Viberg et al., 2020).

This study aims to fill this gap by investigating how UDL influences SRL processes and student motivation in a university context, comparing two courses designed respectively with UDL principles and traditional methodologies. Through the analysis of data from LMS platforms, self-efficacy questionnaires, and academic results, key indicators such as engagement, resource use flexibility, and the reduction of performance disparities will be examined (Bendjebar et al., 2022; Azevedo, 2015). The use of EDM algorithms, such as SVM and decision tree models, will allow for the correlation of independent variables (e.g., use of interactive materials) with educational outcomes, providing concrete evidence to optimize the learning experience (Boulahmel et al., 2025; Al-Azawei et al., 2017).

The expected results highlight not only improvements in inclusivity and accessibility but also a significant impact on perceived self-efficacy and self-regulation capacity,

which are critical for academic success in digital contexts (Zimmerman & Moylan, 2009; Panadero, 2017). This theoretical and methodological contribution reinforces the role of EDM in supporting data-driven pedagogical decisions, promoting adaptive and personalized learning environments.
In line with the stated objectives, this study seeks to address the following research questions:

RQ1: How does implementing Universal Design for Learning (UDL) principles in university courses affect students' Self-Regulated Learning (SRL) processes compared to a traditional instructional approach?
RQ2: What is the impact of the UDL approach on student motivation and engagement, as measured through behavioral data, self-reported perceptions, and academic outcomes?
RQ3: To what extent does Educational Data Mining (EDM) enable the identification of differentiated patterns of self-regulation and motivation among students participating in UDL-based versus traditional environments?

Based on the literature and preliminary evidence, the following hypotheses are formulated:

H1: Students enrolled in courses designed according to UDL principles will exhibit significantly higher levels of SRL than those in traditional courses.
H2: The UDL approach will be associated with greater intrinsic motivation and higher levels of engagement, both behaviorally and as perceived by students.
H3: The integration of EDM will allow for the identification of student clusters with distinct self-regulation and motivation profiles, with more favorable profiles emerging in UDL contexts.

1. Theoretical Background

The concept of Universal Design for Learning (UDL) is based on the idea that education should be designed from the outset to be accessible and flexible, meeting the needs of a heterogeneous student population. The UDL framework, introduced by Rose and Meyer (2002) and later formalized by CAST (2011), is structured around three core principles: multiple means of representation, multiple means of action and expression, and multiple means of engagement. These principles aim to reduce learning barriers, promoting inclusive environments where each student can develop their potential through personalized pathways (Al-Azawei et al., 2017). The application of UDL principles in higher education has been shown to improve student satisfaction, motivation, and engagement, as well as reduce the performance gap between students with and without disabilities (Hall et al., 2015; Kumar & Wideman, 2014). In parallel, Self-Regulated Learning (SRL) is a key construct for understanding how students autonomously and proactively manage their learning process. SRL integrates cognitive, metacognitive, motivational, and emotional components, enabling students to plan, monitor, and reflect on their study strategies (Zimmerman, 1986; Panadero, 2017). Theoretical models such as the cyclical model of Zimmerman and Moylan (2009) and the Winne and Hadwin model (1998) describe SRL as a process articulated in phases: preparation, execution, and reflection, in which motivation and metacognition play central roles. The effectiveness of SRL has been widely associated with better academic results and greater adaptability in digital learning contexts (Azevedo, 2015; Schunk & Zimmerman, 2012). The integration of UDL principles with the analytical potential of Educational Data Mining (EDM) opens new perspectives for the evaluation and optimization of learning processes. EDM applies data mining and machine learning techniques to educational data (LMS logs, academic results, behavioral tracking) to identify patterns, predict outcomes, and personalize instructional interventions (Bisri et al., 2025; Wilken & Adamiak, 2025). EDM applications range from predicting dropout risk to content personalization and the evaluation of engagement and perceived self-efficacy. For example, the use of algorithms such as Support Vector Machine (SVM) and decision trees has proven effective in predicting academic performance and identifying at-risk students, enabling timely and targeted interventions. Recent literature underscores how the combination of UDL, SRL, and EDM is particularly promising for fostering more inclusive, flexible, and personalized learning environments. Sáiz-Manzanares et al. (2020) highlight that the adoption of active and innovative methodologies, supported by digital technologies and data analysis, promotes sustainability and inclusivity in higher education, especially when using mixed approaches (quantitative and qualitative) and techniques such as clustering and text mining to analyze teaching-learning processes. Furthermore, measuring SRL through trace data and learning analytics enables the objective mapping of students' self-regulation strategies and the provision of personalized scaffolding to support motivation and autonomy (Boulahmel et al., 2025). In summary, the theoretical background of this project is based on the intersection of UDL, SRL, and EDM:

- UDL provides the framework for designing accessible and customizable educational environments;

- SRL represents the process through which students exercise agency and control over their learning;
- EDM offers tools for advanced analysis of educational data, enabling empirical and continuous evaluation of instructional strategies' effectiveness.

This synergy is crucial for promoting inclusivity, flexibility, and effectiveness in higher education, addressing the challenges of student diversity and pedagogical innovation.

2. Proposed Psycho-Educational Model

To assess the impact of Universal Design for Learning (UDL) on Self-Regulated Learning (SRL) processes and student motivation through Educational Data Mining (EDM), we have structured an interpretative model of a psycho-educational nature based on the integration of three conceptual axes, each supported by recent scientific literature. The first pillar of the model lies in UDL principles, which promote accessible, flexible learning environments capable of responding to students' differences. The second theoretical axis concerns SRL, representing students' ability to plan, monitor, and reflect on their learning strategies, integrating cognitive, metacognitive, motivational, and emotional components (Zimmerman & Moylan, 2009; Panadero, 2017). UDL, by providing environments rich in resources and opportunities for choice, acts as a catalyst for the activation of more sophisticated self-regulatory strategies, supporting intrinsic motivation and perceived self-efficacy. The effectiveness of SRL has been associated with better academic results and greater adaptability in digital learning contexts. The third pillar is represented by EDM, which enables the analysis of large volumes of educational data (LMS logs, academic results, questionnaires) to identify patterns of behavior, engagement, and performance. Data analysis allows for the objective mapping of SRL strategies, the evaluation of the impact of motivational and engagement variables, and the development of robust predictive models to optimize the learning experience and reduce inequalities.

3. Project Proposal Structure

The project proposal involves comparing two equivalent university courses: one designed according to UDL principles and one using a traditional approach. Students will be monitored through the collection of multimodal data:

- Behavioral, emotional, and cognitive engagement (interactions, accesses, sentiment, participation, study strategies, resource use) via LMS logs and sentiment analysis.
- Perceived self-efficacy and motivation through validated pre- and post-intervention questionnaires.
- Academic outcomes via grades, completion rates, and navigation sequence analysis.
- SRL patterns: planning, monitoring, reflection, use of metacognitive tools.

EDM analysis will integrate machine learning algorithms for performance prediction and clustering techniques to identify SRL and motivation profiles. The mixed-methods approach (quantitative and qualitative) will empirically validate the advantages of UDL, promoting the scalability and replicability of the model in other disciplinary and institutional contexts. This psycho-educational model allows for the empirical evaluation of UDL's impact on SRL and motivation, the optimization of the learning experience through data analysis, and the identification of areas for improvement and personalization of instructional interventions. The systematic adoption of UDL, supported by EDM, can represent an effective strategy to reduce inequalities, promote student autonomy, and support the transformation of educational models towards inclusivity and data-driven approaches.

4. Materials and Methods

Research Design

The project proposal is based on a quasi-experimental parallel group design to compare two equivalent university e-learning courses: one designed according to Universal Design for Learning (UDL) principles and the other using a traditional approach. The aim is to assess the impact of UDL implementation on Self-Regulated Learning (SRL) processes, motivation, engagement, and students' academic outcomes, using Educational Data Mining (EDM) for quantitative and qualitative analysis of the collected data. The research design was developed to test the hypotheses above (H1–H3), ensuring the collection of quantitative and qualitative data required to answer research questions RQ1–RQ3. The comparison between the two groups (UDL vs. traditional) will be guided by the statistical verification of differences in SRL, motivation, and engagement, as well as by the analysis of emerging patterns through EDM.

Participants and Context

The study aims to recruit university students enrolled in two equivalent courses, one with a UDL approach and one traditional, within the same disciplinary field. Selection will be voluntary and based on principles of group homogeneity regarding basic demographic and academic variables (age, gender, academic background).

Ethical Aspects

The study will be conducted by ethical guidelines for educational research, with prior approval from the university ethics committee, informed consent from participants, and anonymization of the collected data.

Educational Intervention

- UDL Course: Designed according to the three UDL principles (multiple means of representation, action/expression, engagement), with materials accessible in various formats (texts, videos, interactive presentations), flexible assessments and opportunities for choice, and timely, personalized feedback.
- Traditional Course: Delivered using conventional frontal methods, with standardized materials, uniform assessments, and less flexibility in access and interaction.

Data Collection

Data collection will occur on three levels:

1. Engagement and SRL: Tracking of interactions on LMS platforms (accesses, time spent, navigation sequences, use of multimedia resources and self-assessment tools).
2. Perceived self-efficacy and motivation: Administration of validated pre- and post-intervention questionnaires, including self-efficacy and learning motivation scales.

3. Academic outcomes: Analysis of grades, activity completion rates, and final assessment results.

Educational Data Mining and Analytical Tools

A mixed-methods approach will be used, integrating quantitative and qualitative techniques:

- Data Mining: Application of supervised and unsupervised machine learning algorithms, including Support Vector Machine (SVM) for predicting academic performance and clustering techniques (e.g., K-means) to identify engagement patterns and SRL profiles.
- Statistical Analysis: Use of descriptive statistics, analysis of variance (ANOVA), and regression models to compare groups on key variables (engagement, self-efficacy, academic outcomes).
- Qualitative Analysis: Thematic analysis of open-ended responses and interaction logs using text mining software (e.g., Atlas.ti) to identify emerging themes related to motivation and self-regulation strategies.

Validity and Reliability

To ensure validity and reliability:

- Validated instruments and scales from the literature will be used to measure SRL, self-efficacy, and motivation.
- Data will undergo cleaning, normalization, and coding processes, following Knowledge Discovery in Databases (KDD) best practices.
- Predictive models will be evaluated using cross-validation and confusion matrix analysis, with indicators such as accuracy, precision, recall, and AUC.

Scales to Be Used

The project proposal includes the measurement of key psychological variables such as engagement, perceived self-efficacy, learning motivation, and SRL processes. The following scales will be used:

- E-learning Self-Efficacy Scale (ELSE): Measures students' perception of self-efficacy in digital environments, validated by Al-Azawei et al. (2017) with high reliability (Cronbach's alpha = 0.815).

- Motivated Strategies for Learning Questionnaire (MSLQ): A validated tool for assessing self-regulated learning strategies and motivation, consistent with the theoretical models of Pintrich and Zimmerman, capturing cognitive, metacognitive, and motivational SRL dimensions (Boulahmel et al., 2025).
- Engagement Scales: For engagement assessment, the literature suggests using multidimensional scales that capture behavioral, emotional, and cognitive components (Chen et al., 2025), integrated with trace data analysis (LMS logs) for objective, triangulated measurement.

These instruments will be administered digitally via the LMS platform, ensuring standardized data collection and integration with behavioral data.

Experimental Design: Three-Stage Research

The experiment will follow a quasi-experimental parallel group design, with data collection at three key points during the university course (initial, midterm, and final).

Initial Phase (T0, baseline)

Administration of psychological scales (ELSE, MSLQ, Engagement) to all students in both groups (UDL and traditional) before the start of instructional activities. Collection of demographic and academic baseline data to ensure group homogeneity. Activation of LMS interaction tracking (accesses, time spent, resource use).

Midterm Phase (T1)

Re-administration of psychological scales to monitor intermediate changes in self-efficacy, motivation, engagement, and SRL strategies. Intermediate analysis of trace data to detect resource usage patterns, access frequency, and participation in educational activities. Qualitative feedback via open-ended questions on the learning experience.

Final Phase (T2, post-intervention)

Final administration of psychological scales to assess outcomes in terms of self-efficacy, motivation, engagement, and SRL. Analysis of academic results (grades, activity completion, exam outcomes). Collection of trace data for the entire course.

Qualitative analysis of open-ended responses and interaction logs using text mining (Atlas.ti).

Data Analysis

Data analysis will be conducted at quantitative, qualitative, and EDM levels:

- Quantitative Analysis: Calculation of means, standard deviations, and distributions for all key variables at the three experimental stages. ANOVA for repeated measures, regression models, and predictive models (e.g., SVM) will be used to correlate psychological and behavioral variables with academic outcomes.
- Qualitative Analysis: Thematic analysis of open-ended responses and interaction logs to identify emerging themes related to motivation, engagement, and self-regulation strategies.
- Educational Data Mining: Application of clustering and machine learning techniques to identify patterns in trace data and profiles of at-risk or highly self-regulated students.

All these techniques will be integrated in a mixed-methods design, where EDM quantitative results will be triangulated with qualitative analyses (text mining, thematic analysis) for a multidimensional understanding of learning processes, as recommended by recent literature.

5. Expected Results

Based on literature analysis and basic computational simulations, the expected results from comparing a university course designed according to UDL principles with a traditional course, analyzed through EDM, can be articulated as follows.

Greater inclusivity and reduced inequalities

UDL implementation is expected to create a more inclusive learning environment, capable of meeting the needs of students with diverse backgrounds, abilities, and learning styles. Empirical studies show that adopting UDL reduces learning barriers and performance disparities between students with and without disabilities, promoting equity and active participation (Al-Azawei et al., 2017; Sáiz-Manzanares et al., 2020).

Increased engagement and motivation

Behavioral data analysis on digital platforms (LMS) is expected to show that students in the UDL course display higher levels of behavioral, emotional, and cognitive engagement compared to the traditional course. EDM enables the identification of richer and more varied interaction patterns, associated with greater motivation and active participation (Chen et al., 2025; Al-Azawei et al., 2017). In particular, the use of multimedia resources, the possibility of choice and personalization, and timely feedback are elements that, according to the literature, increase engagement and intrinsic motivation.

Improved perceived self-efficacy and self-regulation processes

Analysis of questionnaires and trace data relating to self-efficacy and SRL in literature suggests that the UDL group should show a significant increase in perceived self-efficacy and the use of self-regulatory strategies compared to the traditional group (Boulahmel, Djelil, & Smits, 2025). The expected data highlight a positive correlation between the flexibility of the UDL environment and the activation of planning, monitoring, and reflection strategies, which are key elements of SRL.

Better academic results and reduced at-risk students

The use of EDM algorithms, such as SVM and decision trees, enables the prediction of academic results with high accuracy (AUC > 0.9) and the early identification of students at risk of failure or dropout (Bisri et al., 2025; Wilken & Adamiak, 2025). The UDL group is expected to record a higher percentage of students with positive outcomes, reduced delays in exam completion, and fewer dropouts, thanks to more adaptive and personalized teaching.

Empirical evidence on the effectiveness of instructional strategies

The EDM approach allows for the identification of patterns and clusters of students based on interaction, engagement, and performance data, thus providing concrete indications of the relationship between instructional strategies and learning outcomes (Sáiz-Manzanares et al., 2020; Chen et al., 2025). The mixed (quantitative and qualitative) analysis will empirically validate the advantages of UDL, promoting the scalability and replicability of the model in other disciplinary and institutional contexts.

Development of predictive models and personalized recommendations

EDM, integrated with machine learning and text mining techniques, will enable the development of robust predictive models for the personalization of instructional interventions and timely student support (Wilken & Adamiak, 2025; Bisri et al., 2025). These models can be used to optimize curricular design and support strategies, contributing to the development of increasingly inclusive and data-driven learning environments.

Discussion

The expected results for this study are anticipated to confirm that the implementation of Universal Design for Learning (UDL) principles in university courses, analyzed through Educational Data Mining (EDM), brings significant benefits in terms of engagement, perceived self-efficacy, self-regulated learning, and academic outcomes compared to traditional courses. The empirical evidence collected fits within a theoretical and methodological framework that values the adoption of flexible, inclusive, and data-driven instructional approaches, in line with the recommendations of the most recent international literature. The literature shows that UDL adoption is particularly effective in promoting more inclusive learning environments, capable of reducing barriers and meeting the needs of a heterogeneous student population. Systematic reviews highlight that the combination of educational innovation, active methodologies, and technological resources is fundamental to fostering equity and participation (Sáiz-Manzanares et al., 2020). In particular, clusters identified in the literature through data mining techniques show that the inclusion of society, educational innovation, and active methodologies represents the most effective combination for promoting sustainability and social transformation in education. Behavioral data analysis and student perceptions in the literature confirm that courses designed according to UDL principles generate higher levels of behavioral, emotional, and cognitive engagement than traditional courses. The use of multimedia resources, personalized learning pathways, and flexible assessment methods contribute to increased intrinsic motivation and perceived self-efficacy (Al-Azawei, Parslow, & Lundqvist, 2017). EDM, through trace data analysis, machine learning, and predictive models, has proven crucial in the literature for identifying learning patterns, predicting academic results, and identifying at-risk students. However, the literature emphasizes the need to integrate non-cognitive variables (such as motivation and self-efficacy) into predictive models to increase the precision and relevance of interventions. Systematic analysis of SRL measurement practices using trace data shows that UDL models foster the development of more sophisticated self-regulatory strategies, thanks to the presence of digital scaffolding, personalized feedback, and opportunities for choice (Boulahmel, Djelil, & Smits, 2025). Students in UDL environments tend to plan, monitor, and reflect more effectively on their learning than peers in traditional courses, with a positive impact on academic outcomes and motivation.

Limitations and Future Perspectives

Despite the expected results regarding the application of this framework, some limitations must be acknowledged. First, the generalizability of EDM models may be influenced by the specificity of institutional contexts and the quality of available data. Second, the complexity of integrating affective and motivational variables into predictive models remains an open challenge (Boulahmel et al., 2025). Finally, teacher training and the availability of adequate technological resources remain critical factors for the effective large-scale implementation of UDL.

Practical Implications and Recommendations

Based on the analysis, it can be concluded that the systematic adoption of UDL, supported by EDM, can represent an effective strategy to optimize the learning experience, reduce inequalities, and promote student autonomy. The following educational guidelines should be implemented:

- Integrate active and personalized methodologies into university curricula;
- Develop data analysis systems accessible to non-specialists to encourage widespread adoption of EDM;
- Invest in teacher training on the use of technologies and inclusive approaches;
- Promote interdisciplinary collaboration for the design of sustainable and adaptive learning environments.

Conclusions

The proposed framework for optimizing the presented project aims to confirm that the implementation of Universal Design for Learning (UDL) in university contexts, analyzed through Educational Data Mining (EDM), promotes significant improvements in Self-Regulated Learning (SRL) processes, engagement, and academic outcomes compared to traditional approaches. Literature data show that flexible course design, based on UDL principles of multiple representation, differentiated action/expression, and active engagement, leads to a 30% increase in perceived self-efficacy and a 25% reduction in performance disparities between students with and without disabilities (Al-Azawei et al., 2017; Sáiz-Manzanares et al., 2020). Trace data analysis has shown that UDL stimulates metacognitive strategies, such as planning and activity monitoring, correlated with greater persistence in learning (Boulahmel et al., 2025). EDM has proven to be a crucial tool for identifying behavioral patterns related to engagement, such as the use of multimedia resources and the frequency of interactions with personalized feedback, predictive of academic success (Bisri et al., 2025; Wilken & Adamiak, 2025). Predictive models based on machine learning algorithms (e.g., SVM, hierarchical clustering) have achieved accuracy above 90% in predicting outcomes, highlighting the potential of these tools for timely interventions (Chen et al., 2025). However, critical issues arise related to teacher resistance in managing advanced technologies (60% of cases) and uneven access to digital devices, factors that limit implementation equity (Sáiz-Manzanares et al., 2020). To optimize the impact of UDL, it is essential to invest in teacher training on the use of adaptive platforms and the integration of accessible learning analytics systems (Heikkinen et al., 2023). Future research should explore the application of hybrid frameworks combining UDL and generative artificial intelligence (e.g., GPT-4-based chatbots) to further personalize learning pathways and strengthen student agency (Zhou & Hou, 2024). Moreover, extending these models to multidisciplinary contexts and populations with complex educational needs could amplify their scalability and inclusive effectiveness.

Author contributions

Emanuele Marsico: Conceptualization, Investigation, Writing – original draft (paragraphs: Introduction, 1, 2, 3, 4, Dicussion); Muhammad Amin Nadim: Investigation, Writing – original draft, Writing – review & editing (paragraphs: 5, Conclusions); Luigi Piceci: Supervision, Writing – review & editing (paragraph: Conclusions).

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