PREVENTING AND FIGHTING EARLY LEAVING FROM EDUCATION & TRAINING WITH AI

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stAI

Act before it happens: Preventing and fighting Early Leaving from Education and Training with Artificial Intelligence

Mapping the main risk factors of ELET

T2.4 Recommendations about the most effective intervention strategies - including the use of AI technology - to be adopted to prevent and combat ELET

Leader: Emphasys CENTRE

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1. Introduction

1.1. Purpose of the Handbook

The handbook aims to provide actionable, evidence-based guidance to educators, school administrators, policymakers, and other stakeholders to prevent and address Early Leaving from Education and Training (ELET). It seeks to bridge the gap between predictive AI-driven insights and practical, on-the-ground interventions by offering tailored strategies and best practices for reducing dropout rates. By emphasizing knowledge-driven approaches and aligning with local contexts, the handbook serves as a foundational resource for improving decision-making and fostering proactive support mechanisms.

The handbook provides guidance on mitigating risks associated with ELET by presenting effective intervention strategies tailored to address key risk factors. Drawing from transnational and country-specific insights, it educates stakeholders about the role of knowledge-driven AI systems in early detection of at-risk students, highlighting ethical considerations and data privacy principles such as adherence to GDPR. It offers practical frameworks for implementation, including step-by-step methodologies, case studies, and real-world examples to help schools integrate AI-based early warning systems. By translating broad strategies into actionable, localized plans, the handbook ensures its recommendations are suitable for specific national contexts, accounting for cultural, legal, and operational differences. Additionally, it aims to empower educators and school staff with the knowledge and tools to effectively implement AI-driven solutions, fostering capacity building within school ecosystems. Finally, the handbook emphasizes the importance of ethics, data privacy, and transparency in the application of AI technologies to ensure that these systems are implemented responsibly and inclusively.

The handbook is designed for a diverse audience, beginning with educators, school staff, teachers, principals, and counselors who play a central role in identifying and supporting at-risk students. It also targets policymakers at both national and local levels, offering them frameworks to combat ELET effectively. AI practitioners and technologists developing knowledge-driven systems for the education sector will find the handbook valuable for understanding the unique challenges and ethical considerations of applying AI in schools. Researchers and academics interested in the intersection of AI and education will benefit from the handbook's exploration of ethical, social, and practical implications. Additionally, parents and community stakeholders are included, recognizing their critical role in creating a holistic support system for students. Finally, international education organizations can use the handbook to gain comparative insights and foster collaborative approaches to addressing ELET across diverse regions.

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1.2. Definition of ELET

- Explanation of Early Leaving from Education and Training (ELET).
- Importance of addressing ELET.
- The main risk factors leading to ELET in education and the respective preventive measures.

Early disengagement from education and training is a complex problem in several European countries with multiple and variable causes. However, we can assume that family environment or a migrant background, personal, gender and socio-economic circumstances are some of the factors that contribute to early school leaving. There are also several factors linked to the education system that influence early dropout rates. These are the high retention rate, the socio-economic segregation of schools and the early steering of students into different paths based on their academic performance.

Image from: https://eurydice.eacea.ec.europa.eu/sites/default/files/styles/oe_theme_medium_no_c

Early disinterest in education and the lack of qualifications among young people continue to represent a serious social challenge. Although there has been notable progress in recent years, thousands of young people still leave school without completing basic schooling and without the essential skills for their social integration, which puts them at high risk of social exclusion. The dropout rate remains high, intensified by the fact that young people leave school with very few qualifications. Low educational levels are one of the main reasons for youth unemployment and vulnerability to poverty. It is linked to social marginalisation, poverty and even health issues. It is indeed more common for students who dropout of school early to come from family backgrounds marked by socio-economic disadvantage, such as unemployment, low family income and parents with low levels of education.

There are many reasons why some young people early drop out of education or training. Personal or family issues, learning difficulties or unfavourable socio-economic conditions. The structure of the education system, the school environment and the interactions between teachers and students are also relevant elements.

Early dropout has a negative effect on young people's chances of accessing the labour market, consequently resulting in a high cost, not only for individuals, but also for society and the country's economy. Various studies carried out on this issue indicate that early school leaving reduces the chances of entering the labour market, which consequently

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increases unemployment rates, socio-economic losses and health problems, as well as lower participation in political, social and cultural activities.

We are undoubtedly facing a real social crisis. Especially in times of financial crisis, early school leaving causes serious harm to young people. Consequently, these adverse consequences also affect the descendants of those who leave school too early, which can prolong the issue. Since the reasons why young people don't finish school are often complex and interconnected, strategies to reduce early school leaving need to consider various aspects, integrating social and educational policies when working with young people.

Finishing school can result in more and better job opportunities and better health conditions for the individual, not to mention higher productivity rates, lower social and public sector costs, greater economic expansion and greater social harmony.

Tackling the causes of this dropout is fundamental and creating strategies to overcome them has become a crucial issue in Europe. A higher level of education brings benefits to both the individual and society. The advantages of staying in school longer translate into better jobs, better health conditions, fewer offences, greater social cohesion, lower public and social costs, accelerated productivity and growth. However, there are also positive elements that decrease the likelihood of early school leaving, such as high-quality pre-school education, high-quality early childhood care and the efficient management of the processes of moving from primary to secondary education, from secondary to higher education and from the school environment to the labour market. More flexible pathways in secondary education can also have a positive impact on preventing or reducing early school leaving.

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1.3. The Role of AI in Education

Overview of AI technology in education

Artificial Intelligence (AI) began taking its first steps in the 1950s. For many years, its evolution was slow and largely unnoticed by the general public. However, everything changed on November 30, 2022, when OpenAI officially launched ChatGPT, the most famous of the AI tools. In the two years since this groundbreaking event in human history, it feels as though much more time has passed, but it remains a very recent development.

AI is transforming many sectors, and education is no exception. The introduction of this "new" technology is reshaping the way we teach and learn. Naturally, this transition is not easy, especially for teachers who have spent their entire careers teaching in one way, often using similar methodologies. Now, they must adapt to a completely new approach. The first step in this evolution was the introduction of digital technologies in education. While some teachers resisted this change, the situation with AI is fundamentally different. This time, change is inevitable—AI is reshaping everything, regardless of whether we accept it or not. It is no longer something we can stop or reverse.

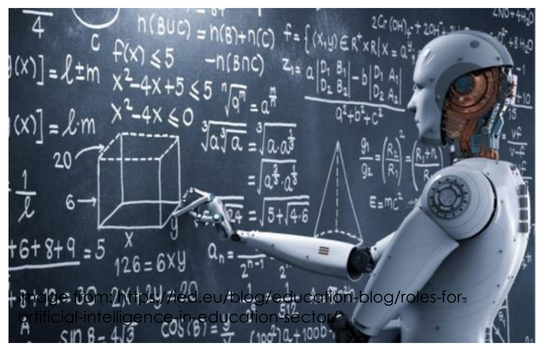
Image from: https://ied.eu/blog/education-blog/roles-for-artificial-intelligence-in-education-sector/

Artificial Intelligence brings immense value to education. For example, it enables personalized learning, which has long been a central goal of many pedagogical approaches. Renowned psychologist Lev Vygotsky made significant contributions to developmental psychology and education, emphasizing the importance of social and cultural contexts in human development. His concept of the Zone of Proximal Development (ZPD) defines the gap between what a learner can do independently (actual development level) and what they can achieve with guidance from a more knowledgeable adult or peer (potential development level). This theory highlights the importance of scaffolding in learning, where educators guide students to achieve higher levels of understanding.

AI can act as this "knowledgeable adult or peer." Of course, this role must always be supervised by a teacher, who acts more like a coach to support students in their learning journey, rather than taking a directive approach.

AI allows for the customization of learning experiences to meet individual student needs, creating a more personalized education. It challenges the traditional paradigm that all

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students must learn the same content in the same way and at the same pace. As we know, students learn at different speeds. The idea of administering the same exam to an entire group of students is inherently unfair, as Albert Einstein famously said. AI has the potential to address this issue by offering opportunities for every student to follow their own learning path.

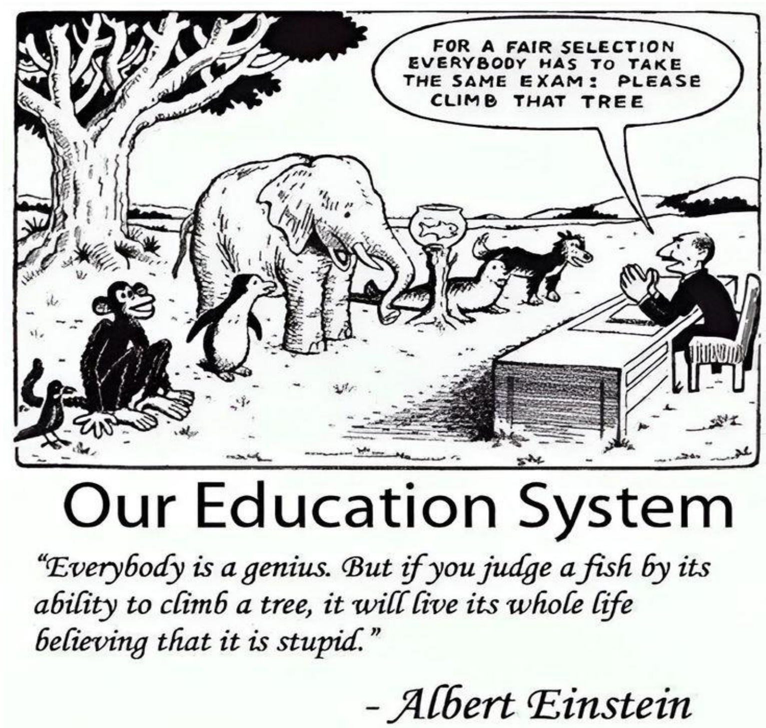

Image from: https://pt.pinterest.com/pin/62135669834161167/

The flipped classroom methodology reverses the traditional teaching model. Students study instructional content (e.g., videos, readings) at home before class and use classroom time for interactive, hands-on activities, discussions, and problem-solving, fostering deeper understanding and engagement.

AI-based early warning system in education

With the introduction of Artificial Intelligence (AI) in education, new challenges have emerged. For teachers, one of the top concerns is how easily students can now cheat, as AI tools make it much simpler. The key is to educate students on the proper use of AI—not as a way to complete their work for them, but as a tutor or support tool. When students rely on AI to do their work entirely, they fail to learn, resulting in a poor level of knowledge. On the other hand, students who use AI as a support, for instance, to create

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a presentation, must verify the accuracy of the content themselves, applying methods such as the flipped classroom[1] approach.

Educators, including teachers, must develop strong knowledge in this area to verify the authenticity of student work. This skill is crucial across all levels of education. As mentioned earlier, AI tools can reduce human participation in content creation, which makes it even more important for teachers to ensure the authenticity and originality of both the content and the work produced by students.

Another growing concern is the issue of AI-generated content being used to feed other AI systems. Many AI-generated materials have the potential to create content, but not all are accurate or true. Special attention must be paid to this issue. Just as we previously needed to address the spread of fake news, particularly on social media, we must now be vigilant about the reliability of AI-generated content.

The potential of AI in monitoring, preventing, and combating ELET

Artificial Intelligence (AI) can provide significant support in monitoring, preventing, and combating Early Leaving Education and Training (ELET).

Monitoring. AI can identify early signs of disengagement or academic struggles in students, predicting potential dropouts. This monitoring can be done individually, tracking various variables, and helping to identify students at risk of ELET. By analyzing student data such as attendance, grades, and behavior, AI can forecast at-risk students and enable timely interventions. These variables may include historical grades, as well as social factors, such as students from disadvantaged socioeconomic backgrounds. In rural areas, for example, students may leave school to help support their families financially or seek independence, which is often seen as the "easier" route.

Early Identification and Fast Action. With AI's support, it is possible to identify at-risk students much faster. Early intervention can make a significant difference, allowing schools to act more efficiently. The ability to monitor student engagement in real-time provides the opportunity to respond quickly, as early action is crucial in preventing ELET.

Personalized Support for At-Risk Students. AI can help create tailored strategies for at-risk students, such as providing deeper tutoring or mentorship when signs of disengagement appear in their daily routine. This real-time monitoring of student behavior and participation allows teachers to receive immediate feedback and take timely action to prevent ELET.

[1] The flipped classroom methodology reverses the traditional teaching model. Students study instructional content (e.g., videos, readings) at home before class and use classroom time for interactive, hands-on activities, discussions, and problem-solving, fostering deeper understanding and engagement.

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Enhanced Communication Channels. AI can enhance communication between students, teachers, and parents, ensuring early identification and intervention. Some signs of disengagement may be more visible at school than at home, as educators typically have more experience in recognizing these issues. Teachers can use AI to communicate these early warnings to parents and other support professionals.

Image from:
https://www.teachearlyyears.com/a-

Emotional Well-Being. AI can also be used to monitor and support students' emotional well-being, which can be a contributing factor to ELET. Early identification of emotional distress or mental health concerns allows schools to provide timely support, addressing factors that may lead to early school leaving.

Integration with School Systems. Schools can integrate AI tools with existing systems (e.g., Learning Management Systems, attendance tracking) to create a comprehensive approach to combat ELET. However, this requires the continuous feeding of data into the algorithm to provide real-time responses. While this will require schools to update and maintain student information, the benefits of having a clearer map of potential ELET cases will be substantial.

Ethical Considerations. One crucial issue is the ethical concerns related to the prevention of ELET using AI. The database used to feed AI systems will contain sensitive student information, and the privacy of students must be safeguarded. It is essential that this data is not made public and that educational institutions ensure the protection of individual student privacy when implementing such systems.

2. Core Recommendations on Preventing and Combating ELET

2.1. Early Identification and Intervention

2.1.1. Traditional Methods

Early identification and intervention for students in European schools focus on recognizing and addressing learning difficulties or developmental concerns as early as possible. Various traditional methods are used across different countries to support children who might need additional help. Below are some common methods used in European schools:

Teacher Observation and Screening

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Teacher observations are often the first step in identifying a child's potential learning or developmental concerns. Teachers are in a unique position to notice early signs of difficulties because they work closely with children on a daily basis.

- **Screening tools:** Teachers use informal methods such as checklists and structured observation tools to document and assess various aspects of a student's development. These might include tools designed to assess early literacy, numeracy, social-emotional development, and behavioral issues.
- **Classroom assessments:** Teachers also observe students' participation and engagement in class activities, which can help identify students who may require additional support. These observations can be based on classroom behavior, social interactions, and how a child approaches learning tasks.

Standardized Testing and Assessment

Standardized testing is an objective and formalized way to assess students' academic abilities, ensuring that learning difficulties or developmental concerns are detected systematically.

- **Cognitive ability tests:** These tests are commonly used across Europe to assess areas such as intelligence, problem-solving skills, and cognitive processing.
- **Early assessments:** In many European countries, standardized assessments are used early in a child's educational journey (typically in preschool or early elementary grades). This ensures that any delays in areas like literacy, numeracy, and language development are identified and addressed early on.

Parental Involvement and Reporting

Parental involvement is essential for understanding the full scope of a child's development, as parents can provide key insights into their child's behavior and challenges outside the classroom.

- **Parent-teacher communication:** Teachers and parents often meet regularly to discuss developmental milestones, academic progress, and any behavioral changes. These meetings are a key platform for identifying concerns early on.
- **Questionnaires and surveys:** Parents are frequently asked to complete detailed questionnaires about their child's emotional and academic well-being. This helps educators gather a more holistic picture of the child's strengths and challenges.
- **Parent education programs:** Some schools also offer educational programs for parents, helping them recognize early warning signs of developmental difficulties in children. This approach strengthens the partnership between home and school.

Early Childhood Education (ECE) Focused Programs

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Many European countries prioritize **early childhood education (ECE)** as a preventive measure to catch developmental delays before they become larger issues.

- **Specialized educators:** In preschools and early childhood education centers, specialized educators are often employed to work with children who show signs of developmental delays. These educators focus on using structured interventions tailored to meet specific needs.
- **Preschool screenings:** Many countries implement preschool screening programs that monitor children's progress in essential developmental areas such as motor skills, language acquisition, and social behavior.

Special Education Needs (SEN) Coordinators

A Special Education Needs Coordinator (SENCO) plays a critical role in managing and supporting students with special educational needs.

- **Monitoring progress:** The SENCO works closely with teachers to monitor and track the progress of students who may have learning difficulties or disabilities.
- **Individualized plans:** For students identified as needing additional support, the SENCO helps create tailored education plans (often called Individualized Education Plans, or IEPs) that outline specific interventions and accommodations.

Speech and Language Screening

Speech-language pathologists (SLPs) are involved in assessing and addressing language-related issues, which are a significant area of focus for early intervention.

- **Routine screenings:** Some European countries implement routine speech and language screenings for young children. This helps identify early language delays and provides a basis for intervention programs.
- **Speech delay identification:** Early identification of language delays allows for timely support, which can improve communication skills and prevent more serious language-based difficulties as children age.

Multi-disciplinary Teams and Referrals

In many European schools, **multi-disciplinary teams (MDTs)** collaborate to provide a comprehensive approach to supporting students with developmental or learning difficulties.

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- **Team collaboration:** These teams often include a range of professionals, such as teachers, school psychologists, counselors, social workers, and special education teachers, all working together to support the child.
- **Referrals to specialists:** If a teacher or school professional suspects a learning difficulty or developmental delay, the child may be referred to a specialist, such as an educational psychologist, occupational therapist, or speech therapist, for further assessment.

Classroom-based Intervention

In response to identified needs, **differentiated instruction** and **tailored interventions** are common approaches in European classrooms.

- **Adapting teaching methods:** Teachers adjust their teaching strategies and materials to cater to the individual needs of students. This can include using visual aids, breaking tasks down into smaller steps, or providing more time for assignments.
- **Targeted support:** Students who struggle with learning might be given additional support, such as one-on-one help or the use of assistive technologies, to help them succeed.

Peer Support Programs

In some European countries, **peer support programs** are introduced to foster a collaborative and inclusive environment.

- **Peer mentoring:** Older or more capable students are trained to assist peers who may face learning or behavioral challenges. This helps create a more supportive classroom environment and allows children with special needs to feel more integrated within their peer group.
- **Social development:** These programs also encourage the social integration of students with special needs, helping them develop stronger relationships and social skills.

School Psychological Services

Some European countries, particularly in Scandinavia and Germany, have established **school psychological services** that work in tandem with teachers to identify and address students' learning and emotional challenges.

- **Psychological assessments:** School psychologists conduct assessments to identify any cognitive, emotional, or behavioral issues that may be affecting a student's learning.

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- **Tailored interventions:** Based on these assessments, school psychologists help develop individualized strategies and interventions that support students' well-being and academic success.

Monitoring and Tracking Systems

Tracking systems are used in some countries to monitor and document the academic and behavioral development of students over time.

- **Longitudinal monitoring:** These systems allow schools to identify patterns or trends in a student's performance, helping them spot issues early on and track improvements as they implement interventions.
- **Data-driven decisions:** The data collected helps schools make informed decisions about the kind of support a student may need, ensuring early interventions are timely and appropriate.

Conclusion

While there are variations in the methods used across different European countries, the overarching goal remains consistent: **early identification** and **intervention** are key to ensuring that students receive the necessary support to succeed academically and socially. These strategies work to create an inclusive educational environment that caters to diverse learning needs, promoting long-term success for all students.

2.1.2. AI-Powered Tools

The implementation of AI-based early warning systems has become a transformative approach to identifying at-risk students and supporting academic success. By leveraging predictive analytics and machine learning (ML) techniques, these systems analyze vast amounts of student data to detect patterns and indicators of potential academic failure or disengagement. This proactive approach enables educators to intervene early with targeted support, improving retention and performance. Various predictive models (e.g., decision trees and neural networks) are commonly used to assess risk factors by examining behavioral, academic, and engagement data. This section explores the practical implementation of these AI-driven systems and highlights examples of predictive analytics and machine learning methods used to effectively identify and support at-risk students.

Profiled Dropout at Risk (PDAR) and Learning Intelligent System (LIS) systems

An interdisciplinary team of researchers from the Universitat Oberta de Catalunya (UOC) has developed an AI solution that makes it possible to identify daily those students who are at risk of failing and can automatically take early action by sending personalized messages to reverse the situation (Baneres, Rodriguez-Gonzalez, & Guerrero-Roldan,

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2023; Bañeres, Rodríguez-González, Guerrero-Roldán, & Cortadas, 2023). According to the researchers, this continuous monitoring helps reduce the time between the first signs of risk and the system's intervention to help prevent students from dropping out.

The technology has been pilot-tested with 581 students enrolled in first-semester courses in a number of the UOC's Faculty of Economics and Business bachelor's degree programs and has been found to reduce dropout rates and increase participation during the semester.

The solution consists of the systems Profiled Dropout At Risk (PDAR) and Learning Intelligent System (LIS) which predicts whether students are at risk of failing based on historical course data and the results of the continuous assessment activities carried out during the current academic year. The LIS system predicts the minimum grade that should be obtained by the student in the next activity based on the previous one and assigns a level of risk of failing. If a high level of risk is detected, the system activates the applicable intervention mechanisms in the form of messages to students. The PDAR model significantly improves monitoring, as it uses data on students' characteristics, their performance during the academic year, and their clicks and other daily actions on the UOC's online campus to generate a daily prediction of the risk of dropping out.

The PDAR model makes predictions based on a decision tree and takes into account the learner's profile information (i.e., number of enrolled courses in the current semester, number of repeated enrollments in the target course, whether the student is a novice learner, and the grade point average of the academic report), performance data within the course, and daily clickstream data about the Virtual Learning Environment (VLE) utilization (i.e., access to the VLE, the classroom of the target course, the resources, and tools; and number of messages read in the forum and teacher's blackboard). The model's outcome is the likelihood of not submitting the ongoing academic activity, which is considered to define the dropout risk. Not submitting an activity is evidence that the learner may drop out eventually from the course.

One of the challenges of this kind of system is to avoid false positives[2]. This error primarily affects students who are not always active in the virtual learning environment. Thus, the PDAR model also takes into account a time window that is automatically calculated based on the academic year, the type of activity, and its difficulty in confirming that a student is really at risk of dropping out. The student must remain in the category of being at risk of dropping out for a given consecutive number of days, which is specified for each activity. If a student is at high risk of dropping out, they are sent an automatic intervention message.

The intervention by the system aims to increase students' motivation, for example by making recommendations on time management, setting short-term goals, or providing

[2] Positives people being wrongly identified by the system as being at risk

information on the possible negative consequences of not completing the activity. It also provides additional learning materials and exercises to help students achieve their goals. In addition, the teaching staff for the course can design and personalize the content of messages and adapt them according to the risk level. Finally, the tool has different dashboards that allow both the teaching staff and the student to individually ascertain their current status and potential risks.

This AI solution gives teaching staff the chance to intervene proactively to address their students' problems (Baneres et al., 2023; Bañeres et al., 2023). In addition, it is a scalable tool that allows teaching staff to comprehensively monitor courses with a high number of students.

QuadC platform

QuadC[3] is a student success platform that helps higher education institutions effortlessly deliver their academic support services to improve student recruitment and retention. QuadC enables institutions to connect students with all their available services including tutoring, mentoring, advising, and counseling services, both online and in-person. QuadC provides hassle-free scheduling, automated student and tutor matching workflows, real-time conferencing tools, asynchronous messaging, Early Alerts for at-risk students, supplemental AI Tutor support, and powerful analytics. These key capabilities significantly increase student retention, enhance student engagement, improve productivity, and streamline operations.

At its core, QuadC software utilizes advanced analytics and machine learning algorithms to process large volumes of student data. As such, the platform enables educators to gain valuable insights, make data-driven decisions, and implement targeted interventions. Here's how.

Data analysis and visualization: QuadC software allows educators to analyze large volumes of student data (e.g., academic performance, attendance records, and engagement metrics). The platform provides intuitive data visualization tools that enable educators to explore trends, patterns, and correlations in the data. This helps identify at-risk students and better understand the factors contributing to their challenges.

Early warning system: QuadC software incorporates an early warning system that helps identify students who may be at risk academically or personally. By analyzing various data points, the system generates alerts and notifications when students exhibit behaviors or patterns that indicate potential challenges. Educators can then take proactive measures to provide timely interventions and support.

Behavioral pattern analysis: The software leverages algorithms to analyze the behavioral patterns of students. By detecting changes in behavior, such as declining engagement

[3] https://www.quadc.io/blog/using-quadc-software-to-identify-at-risk-students

or disinterest, educators can identify at-risk students who may need additional support. This analysis helps educators intervene early and address underlying issues impacting academic performance.

Reporting and monitoring: QuadC software provides comprehensive reporting capabilities that enable educators to monitor the progress and effectiveness of interventions. Educators can generate detailed reports on student performance, attendance, and engagement, allowing them to track trends, measure the impact of interventions, and make data-driven decisions.

Supporting at-risk students: QuadC is also instrumental in supporting students after they have been identified. In doing so, the platform enhances student support, improves academic outcomes, and promotes the overall success and well-being of at-risk students.

Personalized interventions and referrals: QuadC software provides actionable recommendations and personalized interventions based on the specific needs of at-risk students. Educators can access targeted strategies, resources, and suggestions to support student's academic progress and overall well-being. This personalized approach ensures that interventions are tailored to each student's requirements.

Overall, QuadC software offers a range of features and functionalities designed to assist educators in identifying at-risk students. From data analysis and visualization to personalized interventions and collaboration tools, the platform empowers educators with actionable insights and resources. By leveraging the power of advanced analytics and machine learning, QuadC software streamlines the process of identifying at-risk students, ensuring that no one slips through the cracks. Plus, with QuadC's referral feature, educators can refer students to various resources in the platform, such as tutoring software. This feature ensures that if an at-risk student is identified, they can immediately begin receiving the resources needed for academic support.

Machine learning algorithm to identify at-risk students and provide early intervention

Ivy Tech[4], a community college with campuses across Indiana, has over 50,000 students whose daily interactions with the institution have generated over 26 terabytes of stored data. This enormous data warehouse gave them a unique opportunity to ask new questions about student behavior and help them better succeed in the classroom. For that reason, the data scientist team develops a machine learning algorithm[5] to analyze student engagement, predict course outcomes with 80% accuracy, identify at-risk students, and provide early intervention. The team built an algorithm to look for patterns in students' online behavior based on anonymized and aggregated metadata from their

[4] https://www.ivytech.edu/about-ivy-tech/

[5] https://edu.google.com/why-google/customer-stories/ivytech-gcp/

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learning management system. They combine AI and more traditional statistical analysis for more valuable results.

A hybrid model to predict at-risk students

The research paper "The Role of Machine Learning in Identifying Students At-Risk and Minimizing Failure" presents a hybrid model using the ensemble stacking method to predict at-risk students (Pek, Ozyer, Elhage, Ozyer, & Alhajj, 2023). Classic machine learning algorithms were applied such as Naïve Bayes, Random Forest, Decision Tree, K-Nearest Neighbors, Support Vector Machine, AdaBoost Classifier, and Logistic. The data set containing the demographic and academic information of the students was used to train and test the model. The hybrid model with the highest performance was achieved when the SVM was used as a meta-learner, reaching 94.8% accuracy and 96.8% precision.

A framework for predicting the students at risk in higher education institutions

The research paper "A Framework for Predicting the Students at Risk Using AI: A Case Study" proposes a framework for predicting students who are at risk of poor academic performance and supports slow learners in higher education institutions (HEI) (Dharmalingam, Baskar, & Ataullah, 2023). To develop this framework, the authors conducted a case study among the undergraduate students offered in a HEI in Oman. These degrees are awarded by the UK University which is classified as level 6 by the Frameworks for Higher Education Qualifications of UK Degree (FHEQ), Quality Assurance Agency (QAA), UK. The module for this study is selected based on the learning experiences of students registered in undergraduate courses over the last three years, the higher number of registrations, and the higher number of at-risk students. The proposed framework can be embedded into the existing learning management system (LMS) to predict the future progression of students based on their weekly performance in the classroom and periodic completion of in-class activities. This model also promotes active participation in the learning process as an additional benefit.

A logistic regression algorithm made predictions based on typical features such as the weekly in-class activities, weekly quizzes, weekly assignments that are to be done by the students, and the forum post and group discussion activities. The machine learning solution forecasts the progress of the learners using the following tags: "in progress", "not in progress", "needs support" and "highly vulnerable".

RADAR: Rapid Analysis and Detection of At-Risk students with Artificial intelligence-based Response

The RADAR system is another approach to identifying students at risk of falling behind or dropping out of school (Embarak & Hawarna, 2024). The system integrates various

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features, including learners' personality, previous academic performance, current academic concepts progress, and soft skills. Machine learning algorithms are utilized to analyze the combination of data and identify patterns that predict a student's likelihood of falling behind. This approach also leverages Explainable Artificial Intelligence (XAI) to provide transparent and understandable insights into its predictions.

RADAR employs a decision tree approach to predict students at risk based on learner's features. The feature selection algorithm is applied to identify the most relevant features that can accurately predict students at risk of falling behind or dropping out. RADAR identifies at-risk students with an overall accuracy of 82.22%, precision of 86.96%, recall of 80%, and F1-score of 83.33%.

The system effectively employs the identified features to predict students' performance continuously, enabling advisors, administrators, and students to take proactive measures to maintain high academic progress levels. The system is designed to provide automated and continuous monitoring of the student's performance and to notify the relevant parties in case of any deviations.

Early identification of at-risk students using deep learning and explainable Artificial Intelligence

The research paper "Course Success Prediction and Early Identification of At-Risk Students Using Explainable Artificial Intelligence" aims to predict students' grades for a course; predict students at risk of failure based on their overall performance; and identify the factors contributing to these predictions (Ujkani, Minkovska, & Hinov, 2024). These objectives are interrelated and allow for a comprehensive understanding of the factors influencing educational success.

Authors employ various machine learning and deep learning techniques for predicting students' success, along with SHapley Additive exPlanations (SHAP) as an XAI technique, to understand the key factors behind success or failure. Models were trained utilizing the Open University Learning Analytics Dataset[6] (OULAD), which includes information related to student demographics, course enrollments, assessment performances, and interactions within the virtual learning environment. The machine learning techniques used for course grade prediction are Random Forest, Gradient Boosting, k-nearest Neighbors, and Multi-Layer Perceptron. Deep learning techniques were applied to predict at-risk students, such as Convolution Neural Networks and Long Short-Term Memory, and classical machine learning methods such as eXtreme Gradient Boosting (XGBoost).

This approach enables targeted interventions to support students' success. Results reveal that student engagement and registration timelines are critical factors affecting

[6] https://analyse.kmi.open.ac.uk/open_dataset

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performance. The customized shallow architecture of a multi-layer perceptron achieves up to 94% accuracy for the designed tasks, outperforming traditional approaches and deep learning models. This study contributes to the use of AI in education and offers practical insights not only for educators but also for administrators and policymakers to enhance the quality and effectiveness of online learning.

Predicting at-risk students in the early stage of a blended learning course via machine learning using limited data

In (Azizah, Ohyama, Zhao, Ohkawa, & Mitsuishi, 2024), Azizah et al. focused on detecting at-risk students in a blended learning[7] course. Several motivational variables were analyzed to determine their effect on student performance. They used a machine-learning classifier to compare two approaches: 1) the benchmark study, which uses data from the same academic year for both training and testing; and 2) a prospective study, which focuses on extrapolating a model trained on the previous fall semester to predict outcomes for the upcoming fall semester.

Predictions were made taking into account variables related to interaction with the course (e.g., watched videos, quizzes taken, audio recordings, learning sessions, and duration of engagement) and motivational variables, such as:

- <u>Early learning</u>: Reflecting students' proactive and motivated behavior in initiating their learning activities without delay
- <u>Study in time</u>: Measure students' regular and timely study sessions, which indicate their discipline and early-learning approach
- <u>Catch-up</u>: Focuses on closing the learning gap by acquiring missed knowledge or skills resulting from the absence of prior learning or its inadequacy
- <u>Study again</u>: Captures the review frequency to highlight the importance of restudying for enhancing retention and comprehension

The Shapley additive explanations (SHAP) method emphasizes the importance of time-management variables, particularly study in time, for identifying at-risk students. Random Forest was the classifier applied in both approaches.

Early recognition System with Machine Learning to support Students' Success

An early recognition system equipped with real data captured in a blended learning course is presented in (Ciolacu, Tehrani, Binder, & Svasta, 2018). This system identifies and informs the students with problems by training neuronal networks and Support Vector Machine models halfway through the semester. Models are trained based on online log

[7] Blended learning (BL) is an instructional method that combines on-line learning with face-to-face (F2F) interactions

data extracted from Moodle[8] activities and sensor data obtained from smart sensors (e.g., camera, fingerprint, gyroscope, light, and heart rate). Two types of experimental studies have been conducted: predicting students for a new semester and live recognition of students at risk.

The early recognition system has allowed to reduce the examination failure rate by almost half. This idea contributes strongly to students' performance and provides them with a transparent view.

An AI System for Identifying and Preventing Student Dropout at the National Learning Service in Colombia

A system for identifying student dropouts at the National Learning Service[9] (SENA) in Colombia is presented in (Brand C, Gabriel Ramirez, Diaz, & Moreira, 2024). Machine learning models (e.g., decision trees) are trained based on personal, academic, socioeconomic, and institutional variables that influence student dropout. The decision tree classification technique emerged as the most effective, achieving an accuracy of 91%. The feature analysis highlighted the significance of socioeconomic factors in apprentice dropout, revealing a notable impact on dropout rates, especially in Higher Education Institutions. The prompt identification of these characteristics through Machine Learning classification algorithms has the potential to substantially reduce high dropout rates in technical and professional level training programs facilitated by SENA technology.

AI student success predictor: Enhancing personalized learning in campus management systems

An AI Student Success Predictor is introduced by (Shoaib et al., 2024). This system, empowered by advanced machine learning algorithms, is capable of automating grading processes, predicting student risks, and forecasting retention or dropout outcomes. A Convolutional Neural Network (CNN) feature learning block was applied to extract the hidden patterns in the student data, mainly described through the following features: age, gender, prior education, campus distance, subject code, and credit hours, among others. This classification model stands as an ensemble masterpiece, incorporating SVM, Random Forest, and KNN classifiers, subsequently refined by a Bayesian averaging model. The proposed ensemble model shows the ability to predict the student grades, retention, and risk levels of dropout. The model evaluation results in a 93% accuracy for student grade prediction and student risk prediction, and a 92% accuracy for the challenging domain of retention and dropout forecasting. The proposed AI system seamlessly integrates with existing Campus Management System

[8] https://moodle.org/?lang=en

[9] https://www.sena.edu.co/en-us/pages/default.aspx

infrastructure, enabling real-time data retrieval and swift, accurate predictions, enhancing academic decision-making efficiency.

Evaluation of student failure in higher education by an innovative strategy of fuzzy system combined optimization algorithms and AI

In (Nie & Ahmadi Dehrashid, 2024), different machine learning algorithms along with a conventional adaptive Neuro-Fuzzy Inference System (ANFIS), are used to improve students' classification performance and result prediction. The suggested approach enables dropout forecasting and intervention by providing many learning pathways to ensure students' success and lower failure in higher education institutions. Demographic, socioeconomic, macroeconomic, and academic data at enrollment were taken into account for the prediction.

Smartschool uses AI to detect learning problems

Smartbit is the developer behind Smartschool[10], a digital school platform for primary and secondary education in Belgium. The ambition of the digital school platform Smartschool is to promote cooperation between school management, teachers, students, and parents because a good interaction between all these parties increases the involvement and ultimately the school results of the child[11].

"Some students drop out at a certain point during their secondary school years"[12], says Jan Schuer, founder and CEO of Smartschool. However, these signals are often noticed too late. That is why Smartschool has been working on a 'smart signal function' for two years.

Smartschool takes the use of Artificial Intelligence to detect possible learning disabilities in students a step further. The AI approach looks at three parameters. A student's usage activity on Smartschool is one of them (i.e., how often he or she logs in). The other sources are school results and absences. The goal is to help teachers pick up signals of learning disabilities more quickly, without the technology replacing their work. It is up to the schools themselves to determine who will receive that signal. The students themselves and their parents will not be automatically informed. As CEO Jan Schuer says[13]: "AI helps to flag issues, but it remains up to the teachers to decide how to deal with them."

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[10] https://www.smartschool.be/

[11] https://www.agoria.be/nl/diensten/expertise/talent/develop/onderwijs/innovation-and-digitisation-education/smartschool-ontwikkelaar-smartbit-pleit-voor-betere-publiek-private-samenwerking

[12] https://www.hln.be/onderwijs/smartschool-gaat-leerproblemen-opsporen-via-artificiele-intelligentie~a387060ad/?cb=46e31a49-eee3-4f9e-a074-0d37842570d1&auth_rd=1De&referrer=https%3A%2F%2Fwww.smartschool.be%2F

[13] https://www.smartschool.be/2024/10/smartschool-speurt-via-ai-naar-leerproblemen/

After a trial period in ten secondary schools, the launch of the AI system is planned for 2025. With this AI solution, Smartschool wants to help schools and teachers to intervene more quickly in learning problems, without losing sight of their professional judgment.

Core takeaways

The reviewed research papers, web pages, and news offer valuable insights into the challenges and solutions related to AI-based early warning systems to identify at-risk students. Key findings highlight innovative approaches, emerging trends, and potential areas for improvement within the field. These studies collectively emphasize the importance of identifying relevant variables, establishing the time frames to be considered, choosing accurate machine learning methods, and providing explanations of predictions. However, there is a noticeable gap in the analysis of ethical considerations during the development of these intelligent systems. The insights gained from the reviewed papers and applications provide a foundation for future research and practical applications.

Besides, most research and applications primarily focus on predicting at-risk students in higher education, with an emphasis on forecasting success or failure in specific courses. Additionally, many approaches concentrate on analyzing features derived from online learning platforms (e.g., Moodle and Smartschool) and blended learning environments.

The analyzed research and applications predominantly utilize classical machine learning methods, such as decision trees and support vector machines. To enhance predictive performance, some researchers advocate for the use of ensemble methods, which combine multiple models to improve accuracy and robustness. Additionally, deep learning techniques, including convolutional neural networks (CNNs), have been employed for feature preprocessing, representation, and prediction tasks. The selection of appropriate methods is influenced by various factors, particularly the volume and quality of available training data.

2.2. Enhancing School Environment and Student Well-being

2.2.1. Traditional Strategies

In European schools, traditional strategies for enhancing the school environment and promoting student well-being focus on creating a positive, inclusive atmosphere where students feel safe, supported, and motivated. These strategies often integrate academic, social, emotional, and physical well-being to ensure that students thrive in both their educational and personal development. Below are several key traditional strategies used in European schools to foster such an environment:

Positive Behavior Support Systems

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Many European schools employ positive behavior reinforcement systems where students are recognized for their positive behaviors rather than punished for negative ones.

Classroom rewards, student recognition programs, and behavioral contracts are used to encourage respectful, responsible, and safe behavior.

In many countries, schools often use reward systems (such as stars or certificates) to motivate students and create a sense of achievement and self-worth.

School-Supported Emotional and Mental Health Programs

Schools are increasingly focusing on the mental health and emotional well-being of students. These programs aim to reduce stress, prevent bullying, and provide support for students facing personal challenges.Counseling services: Many schools across Europe provide on-site counseling to students, where school psychologists or counselors offer support for personal issues, anxiety, and family problems.

Peer support programs: In some countries like the UK and the Netherlands, peer mentoring or buddy systems are implemented, where older students support younger students, providing guidance and helping them navigate challenges.

Physical Activity and Outdoor Learning

Physical well-being is an essential part of the school environment in many European countries. Physical education (PE) and outdoor activities are strongly encouraged as part of the curriculum.

Schools in countries like Denmark and Finland place a high value on outdoor learning and physical activity, ensuring students spend time outside every day, whether for recess or structured activities.

Programs such as "Green Schools" in Ireland and outdoor classrooms in Scandinavian countries promote an active lifestyle and a closer connection with nature, helping students develop both physically and emotionally.

Promoting Inclusivity and Diversity

Inclusivity is a key value in many European school systems, with a focus on creating environments where every student feels respected, regardless of their background.

Anti-discrimination education and cultural diversity programs are widespread, particularly in multicultural countries such as France, the UK, and the Netherlands.

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Schools often celebrate diverse cultural holidays and provide opportunities for students from different backgrounds to share their traditions and experiences, which fosters a sense of belonging and mutual respect.

School Safety and Anti-Bullying Initiatives

Many European schools have a zero-tolerance policy on bullying and implement strict anti-bullying programs to ensure that students feel safe.

Bullying prevention programs: In countries like Sweden and Norway, schools implement comprehensive bullying prevention programs that include clear policies, student education, and staff training.

Conflict resolution and mediation: In some regions, peer mediation programs are employed to help students resolve conflicts independently, promoting empathy, communication skills, and respect for others.

Parental Involvement

Schools across Europe encourage strong parental involvement in school life as part of their strategies for enhancing student well-being. Parental engagement is recognized as crucial for improving student outcomes and creating a supportive environment.

Regular parent-teacher meetings, school councils, and community events foster collaboration between families and schools. This relationship helps in better understanding and addressing students' needs.

Parent workshops on topics like child development, positive discipline, and mental health are common in many countries, offering families resources to support their children's well-being.

Student Voice and Participation

Many schools in Europe encourage student voice and active participation in decision-making processes. This can include student councils or regular meetings where students provide input on school policies, the learning environment, or extracurricular activities.

In many countries, students are often consulted on issues that affect them, which gives them a sense of ownership and responsibility in their school community.

This participatory approach not only enhances the school environment but also promotes a sense of empowerment and self-efficacy among students.

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Mindfulness and Stress-Reduction Programs

In recent years, mindfulness and stress-reduction programs have been integrated into European schools as a traditional strategy for enhancing well-being.

Schools in countries like Germany and the UK have introduced mindfulness exercises, breathing techniques, and relaxation sessions into the daily schedule to help students manage stress and improve focus.

These practices encourage emotional regulation, resilience, and overall mental well-being, especially during periods of academic pressure.

Creating a Collaborative and Supportive Classroom Environment

The classroom environment plays a significant role in enhancing student well-being. Teachers are trained to create a positive, inclusive, and cooperative atmosphere in the classroom where students feel safe to express themselves.

In countries like Finland, the emphasis on cooperative learning and group work encourages positive peer relationships and collaboration, reducing competition and fostering mutual support.

Flexible seating arrangements, personalized learning, and emotional check-ins are strategies used to create a supportive, student-centered environment.

Integrated Support Services

In many European schools, integrated support systems are in place, where teachers, social workers, counselors, and other professionals work together to meet the diverse needs of students.

School-based health services are available in several countries (e.g., France, Germany, Spain) to provide on-site health care and emotional support, reducing barriers for students in need of assistance.

This holistic support approach ensures that students receive comprehensive care for their academic, emotional, and physical well-being.

Sustainable and Healthy School Environments

Sustainable schools focus not only on environmental issues but also on promoting the health and well-being of students.

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In many parts of Europe, such as in the Netherlands and Sweden, schools implement green practices, such as reducing waste, promoting healthy food options, and maintaining eco-friendly facilities.

Nutrition programs: Many schools provide students with healthy meals and snacks, aiming to improve both physical health and cognitive function.

Well-being Education

In countries like Norway and Finland, well-being education is integrated into the curriculum to promote self-awareness, social skills, and resilience.

Programs often include life skills education, social-emotional learning (SEL), and conflict resolution training, equipping students with tools to handle challenges and make responsible decisions.

Collaborative Partnerships with External Organizations

Schools in many European countries form partnerships with external organizations such as non-profits, health services, and community groups to support student well-being.

These collaborations offer students access to a broader range of services, including mental health support, sports programs, and extracurricular activities that enhance their overall development.

Conclusion

Traditional strategies for enhancing school environments and student well-being in European schools often revolve around fostering positive relationships, promoting inclusivity, supporting emotional and physical health, and creating environments that allow for active student participation. Each country has tailored its approach based on cultural values, but common themes of support, respect, and collaboration are consistent across the continent.

2.2.2. AI-Powered Tools

Students often face stress during their academic journey, and persistent stressors can result in chronic stress, negatively impacting their physical and mental health, and consequently influencing early school leaving. Therefore, the field of academic stress detection has gained significant attention recently because mental and physical health is crucial for academic success (Abd-Alrazaq et al., 2024; Liu, Zhang, Zhao, & Liu, 2024). The goal of academic stress detection is to identify a student's level of stress during the learning process using observable markers including physiological, behavioral, and

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psychological data. In recent years, detection methods that utilize wearable and nonwearable sensors have gained increased attention owing to their rich functionalities (S. Liu, Zhang, Zhao, & Liu, 2024).

In exploring AI applications in monitoring student well-being (e.g., emotional analysis, stress detection), several research papers offer valuable insights and contribute to the broader understanding of the issue. Some approaches are mainly focused on detecting emotions (Anwar, Rehman, Nasralla, Khattak, & Khilji, 2023; Khare, Blanes-Vidal, Nadimi, & Acharya, 2024; Vistorte et al., 2024), while others aim at detecting stress (Alexios-Fotios A. Mentis, Lee, & Roussos, 2024; Gedam & Paul, 2021; Panda, Sharma, & Jaiswal, 2024) and depression (Joshi & Kanoongo, 2022). These studies address various aspects, methodologies, and applications related to data acquisition, different kinds of features and signals, real-time data analytics, and machine learning approaches to be applied, providing a comprehensive overview of current trends and emerging challenges. The following papers highlight key findings and advancements, offering a deeper perspective on students' mental health monitoring.

The analysis of facial expressions, images, emotional chatbots, and texts on social media platforms has been effective in detecting one's emotions and then depression (Joshi & Kanoongo, 2022). Naive-Bayes, Support Vector Machines (SVM), Long Term Short Memory (LSTM) – Radial Neural Networks (RNN), Logistic Regression, Linear Support Vector, etc. are the various ML techniques used to recognize emotions from text processing; Artificial Neural Networks (ANN) have been used for feature extraction and classifications of images to detect emotions through facial expressions. Sentiment analysis has also emerged as a promising tool to detect and classify emotions expressed in textual and visual forms (Anwar et al., 2023).

A Facial and Vocal Expression Based Comprehensive Framework for Real-Time Student Stress Monitoring in an IoT-Fog-Cloud Environment

A novel IoT-aware student-centric stress monitoring and real-time alert-generating framework to predict student stress index in a particular context is presented in (Singh et al., 2022). This approach uses extended VGG16, Bidirectional Long Short Term Memory network (Bi -LSTM), and Multinomial Naïve Bayes techniques to generate the scores of emotions from student facial expressions, speech pitch, and content of student speech at the cloud layer. Specifically, the model aims to classify the stress events as normal or abnormal based on the overall emotion of the students' physiological data readings. The activation of the abnormal event in case of higher values for negative emotions like stress, fear, sadness, disgust, etc.; a stern alert is sent to the student, coordinators, and caretakers. The raw data was collected from IoT-enabled input devices like smart video cameras, smartphones, and microphones installed around the student under observation. This framework will ultimately be a great tool that will support the education

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institutions, students, their parents, and guardians to get a real-time alert on students' overall emotions.

Towards Emotionally Aware AI Smart Classroom: Current Issues and Directions for Engineering and Education

A smart classroom system is proposed by (Kim, Soyata, & Behnagh, 2018). This system is capable of making real-time suggestions to an in-class presenter to improve the quality and memorability of their presentation by allowing the presenter to make real-time adjustments/corrections to their non-verbal behavior, such as hand gestures, facial expressions, and body language. Suggestions are based on existing research in affect sensing, deep learning-based emotion recognition, and real-time mobile-cloud computing. The smart classroom system uses a three-component architecture: (i) a data acquisition component to receive raw audio/video information, (ii) a pre-processing component to perform initial computations on the received data, and (iii) a massively parallel computing component to perform the high-intensity computations, required by the proposed algorithms.

A Shrewd Artificial Neural Network-Based Hybrid Model for Pervasive Stress Detection of Students Using Galvanic Skin Response and Electrocardiogram Signals

A hybrid model for pervasive stress detection using real-time data analytics and the Internet of Things is presented in (Tiwari & Agarwal, 2021). This approach detects stressful conditions of the student and diagnoses whether they are relaxed, stressed, partially stressed, or happy. Regular monitoring of students' health, including measurement of Galvanic Skin Response (GSR) and Electrocardiogram (ECG) data, provides a good understanding of their stress levels. The graphical relationship between heart rate, blood pressure, and skin conductance across various experimental activities highlights the fact how physiological parameters of the human body get affected along with the mental status of the students. This approach makes predictions based on machine-learning models such as Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Bagging Classifiers (BAG), Random Forest (RF), Gradient Boosting (GB), and Artificial Neural Network (ANN), where the shrewd ANN-based hybrid model achieves 99.4% accuracy on the self-generated dataset for the mental state classification of the students.

Deep Learning-based Mental Health Monitoring Scheme for College Students Using Convolutional Neural Network

A deep learning-based mental health monitoring scheme (DL-MHMS) for college students is proposed (Chao Du, Balamurugan, & Selvaraj, 2021). This model uses a convolutional neural network (CNN) to classify the mental health status as positive, negative, and normal using the EEG signals collected from college students. The simulation analysis achieves the classification accuracy and F1 scores of 97.54% and 98.35%.

Psychological Health Assessment and Intervention System for Chemical Engineering Students Based on Emotional Computing Technology

A novel Psychological Health Assessment and Intervention System tailored for chemical engineering students, leveraging Emotional Computing Technology enhanced by Cartesian Feature Weighted Emotional Classification (CFWEC) is presented in (Zhao, 2024). The system aims to assess students' psychological well-being by analyzing emotional cues extracted from various sources such as facial expressions, voice patterns, and text interactions. The CFWEC model achieved an average accuracy rate of 85% in identifying students at risk of psychological distress, enabling timely interventions. Additionally, the system provides personalized recommendations and interventions based on individual emotional profiles, leading to improved mental health outcomes. These findings underscore the potential of Emotional Computing Technology with CFWEC in promoting psychological health and well-being among chemical engineering students.

Analysis of Educational Mental Health and Emotion Based on Deep Learning and Computational Intelligence Optimization

A new psychological and emotional dataset for the field of education was built as a result of the research presented by (J. Liu & Wang, 2022). The authors also built a mental health stress detection model with an emotional analysis function based on the created dataset. Deep learning and computational intelligence optimization, specifically Ant Colony Optimization (ACO), were applied to detect stress. In conclusion, schools need to pay special attention to obsessive-compulsive disorder and interpersonal sensitivity.

3. Implementation Strategies

3.1. Integrating AI into Existing Educational Frameworks

Integrating AI into Existing Educational Frameworks: Implementation Strategies for Primary and Secondary Levels

To effectively integrate AI tools into current educational practices in primary and secondary schools, it's essential to understand the structure of educational frameworks and align AI initiatives with established goals such as student well-being, personalized learning, and data-driven decision-making.

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The use of AI in higher education is a relatively new phenomenon, and there is still much to learn about how best to integrate it into teaching and learning environments. Empirical-based investigations can help identify the most effective ways to implement AI in higher education and determine the factors that contribute to successful AI integration (Marengo, 2023).

Generative AI (GAI) can revolutionize education by introducing innovative, personalized, and efficient practices. It offers the ability to tailor learning experiences to individual student needs, providing customized feedback, adaptive learning paths, and specialized support for language learning. GAI enhances content creation by automating the development of quizzes, assignments, interactive simulations, and multimedia resources. By integrating these capabilities, it fosters student engagement and introduces immersive learning environments, such as virtual and augmented reality simulations (Mittal et al., 2024).

The integration of AI in education offers several benefits, including enhanced conceptual understanding, personalized instruction, improved engagement and motivation, and efficient assessment and feedback. However, it also poses challenges, such as the need for technical infrastructure, training for teachers, ensuring data privacy and security, and addressing ethical considerations (Mahligawati, 2023).

Researchers have proposed several frameworks and strategies to align AI tools with current educational practices. Schleiss et al. (2023) developed a course planning framework, a tool that addresses the context of domain specific AI-education. According to the researchers, conducting more systematic research on pedagogical approaches for domain-specific AI education and interdisciplinary education would contribute significantly to the field's development.

Using of AI to enhance equity in education is another important aspect, in particular through personalized learning that provides accessibility to all students, but in particular those with disabilities (Roshanaei, 2023).

3.1.1 Key Implementation Steps

Understanding Educational Frameworks and Goals

Educational frameworks often center around academic achievement that is measured through a) standardized testing, coursework, and student engagement, b) social-emotional learning involving supporting students' emotional health and promoting inclusivity, c) early identification of students at risk of absenteeism through monitoring and interventions and d) engaging parents to create a holistic support system for students. To

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align AI tools with these goals, integration of AI tools must emphasize ethical practices, transparency, and the enhancement of teacher autonomy rather than replacing human decision-making.

Step 1: Needs Assessment and Goal Definition

- **Current System Analysis**: Identify challenges in the school (e.g., high dropout rates, lack of real-time data, overburdened staff).
- **Stakeholder Engagement**: Include teachers, parents, administrators, and students to define the intended benefits of AI (e.g., early identification of struggling students or reducing ELET).

Step 2: Infrastructure Readiness

- **Data Management**: Schools must establish robust data storage and processing systems, ensuring interoperability between AI platforms and existing student information systems.
- **Technology Access**: Ensure that necessary hardware (e.g., computers, smart classroom equipment) and internet access are in place, especially in rural or underfunded schools.

Step 3: AI tools and Integration

- **Early Warning Systems (EWS)**: Similar to PDAR (Baneres, Rodriguez-Gonzalez, & Guerrero-Roldan, 2023) and QuadC[14] these systems analyze attendance, grades, and engagement to predict dropout risk and suggest interventions.
- **Accessibility and inclusivity:** AI-powered platforms like Atlas Primer[15] enhances accessibility and inclusivity by converting text into speech and allows students to engage with materials in various settings, promoting continuous learning beyond the classroom.
- **Behavior Analysis Platforms**: Platforms that detect changes in learning behavior (e.g., Smartschool[16]) can complement school practices by alerting teachers when students show signs of disengagement.
- **Learning Management System (LMS) Integration**: Systems like RADAR (Embarak & Hawarna, 2024) and QuadC can be developed to provide real-time updates.

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[14] https://www.quadc.io/
[15] https://www.atlasprimer.com/
[16] https://www.smartschool.be/

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Step 4: Staff Training and Capacity Building

- **Professional Development**: Teachers and administrators need training on interpreting AI-generated insights, understanding model limitations, and making appropriate decisions based on recommendations.
- **Iterative Feedback Loops**: Create channels for continuous feedback from educators and IT staff to refine AI implementations.

Step 5: Ethical and Transparent Implementation

- **Privacy and Data Security**: Adhere to regulations for data protection, ensuring student data is anonymized where possible and used responsibly.

Step 6: Student and Parent Engagement

- **Transparency**: Communicate the purpose and benefits of AI tools to parents and students to build trust and mitigate fears of surveillance.
- **Feedback Mechanisms**: Provide opportunities for students and parents to share concerns and feedback on the system's effectiveness.

Step 7: Monitoring and Continuous Improvement

- Use analytics dashboards to track the system's performance, intervention outcomes, and student progress.
- Conduct regular audits to detect biases or inaccuracies in predictions, ensuring that AI tools serve all students equitably.

Adapting AI for Primary vs. Secondary Schools

- **Primary Schools**: Emphasis should be placed on basic attendance and participation patterns, social-emotional development, and early detection of learning disabilities. AI tools focusing on emotion and stress detection, such as IoT-based frameworks for classroom monitoring (Singh et al., 2022), can complement SEL goals.
- **Secondary Schools**: At this level, AI can provide predictive insights on course performance, attendance, and future academic success, as well as career counseling support based on students' performance patterns and interests.

Challenges and Solutions

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- **Teacher Overload**: AI platforms must streamline rather than complicate workflows. AI systems that integrate scheduling, mentoring, and intervention tools in one interface can reduce administrative burden.
- **Bias and Inequity**: AI tools must be carefully monitored to avoid reinforcing biases present in historical data. Employing Explainable AI methods, like SHAP (Ujkani et al., 2024), helps educators understand and address potential biases.

Recommendations for Policy and Practice

- **Cross-Sector Collaboration**: Collaborations with national and local educational authorities to create guidelines for AI implementation that align with broader policy goals.
- **Pilot Testing and Scale-Up**: Small-scale pilot programs in selected schools to identify best practices before expanding to larger districts.
- **Incorporating Student Voice**: Involving student representatives in discussions about AI-based interventions to ensure tools respect student agency and address their real needs.

By aligning AI integration with existing educational goals, such as early intervention and student well-being, schools can leverage technology to enhance learning outcomes. The key lies in balancing technological innovation with human-centered approaches, ensuring that AI complements and empowers teachers rather than replacing their critical role in the educational process.

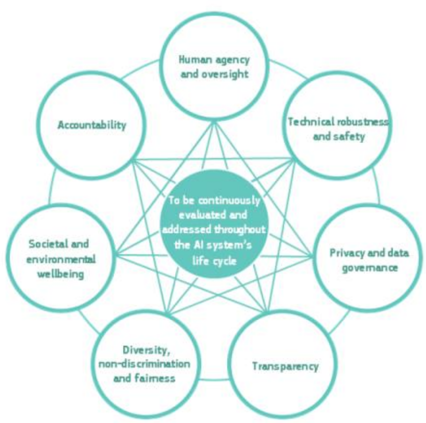
3.2. Ensuring Ethical and Equitable Use of AI

This section, as part of a report on effective intervention strategies—including the use of AI technology—to prevent and combat Early Leaving from Education and Training (ELET), begins with a critical question: **To what degree do AI system decisions influence organisational decision-making processes?** Answering this question is crucial for assessing the risks associated with AI systems and their ethical considerations. According to the **EU AI Act**[17], AI systems used in education are not inherently classified as high-risk. However, their risk level can vary depending on the specific use case, particularly the outcomes derived from AI analysis. This clarity will guide the design and implementation of steps to address detected ELET risks effectively. Clear steps and initiatives must be outlined to act when ELET risks are detected.

The European Union emphasizes the importance of ethical and equitable AI through various official documents and guidelines, setting limitations and defining rights to govern the digital transformation era. Central to this effort is the **Ethics Guidelines for Trustworthy Artificial Intelligence**[18], developed by the High-Level Expert Group on AI.

The guidelines highlight that achieving trustworthy AI requires ongoing efforts across an AI system's life cycle. Key requirements include evaluating implementation methods and continuously assessing and justifying changes to processes, given AI's dynamic and evolving nature.

Seven Key Requirements for Trustworthy AI



As seen above, the guidelines outline seven key requirements for trustworthy AI. These include ensuring that **1) human agency and oversight** are maintained by empowering individuals to make informed decisions while protecting their fundamental rights. AI systems must be **2) technically robust and secure**, incorporating mechanisms for reliability, safety, and fallback options to minimize harm. **3) Privacy and data governance** are equally critical, demanding full respect for privacy, proper data integrity, and legitimized access. **4) Transparency** is essential, as systems and their decisions must be explainable and understandable to all stakeholders. **5) Diversity, non-discrimination, and fairness** must be upheld to avoid biases that could lead to marginalization or

[17] https://www.coe.int/en/web/artificial-intelligence/the-framework-convention-on-artificial-intelligence
[18] https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

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discrimination. AI systems should contribute to **6) societal and environmental well-being** by promoting sustainability and inclusivity. Lastly, **7) accountability** mechanisms, such as auditability and accessible redress, must ensure responsibility for outcomes, especially in critical applications.

In the context of Education, the document mentions the opportunities derived from using AI as it offers transformative potential in education by personalizing learning experiences, improving educational quality, and addressing inequalities. For instance, the stAI project aligns with EU guidelines to reduce ELET while respecting children's rights. AI can enhance learning speed and quality across all educational levels, helping students acquire skills suited to their abilities. However, ethical concerns, such as the automatic identification of individuals, demand careful scrutiny. While identification may align with ethical principles in specific contexts, such as reducing ELET, it raises significant legal and psychological concerns. AI systems must ensure proportional use of control techniques to uphold the autonomy and rights of European citizens. The use of AI in schools must rely on meaningful, verifiable consent from children and their guardians, emphasizing education as a fundamental right.

To address these, proportional control techniques must respect **autonomy and fundamental rights**. Consent mechanisms—appropriate to the age and understanding of children—are necessary when applying AI systems in schools. Moreover, **privacy and data protection**, as mandated by **GDPR**, require robust safeguards such as data minimization and attention to **sensitive data**. These principles advocate for ensuring that AI research respects the highest ethical standards and adheres to relevant EU laws.

In practical terms, this means research initiatives must not exploit sensitive data solely for study purposes. For instance, in cases involving information on **ethnicity or origin**, such sensitive data must be handled with special care. Additionally, the use of **emotional recognition technologies** is prohibited under the **EU AI Act** (Article 5F).

The concept of <u>embedding ethics directly into AI design</u>, known as "**X-by-design**," is critical to achieving trustworthy AI. This approach ensures that abstract ethical principles are concretely linked to implementation decisions. For example, privacy-by-design and security-by-design methods incorporate safeguards into AI systems from the outset, making them secure, robust, and fail-safe. AI systems providers must anticipate and address potential risks and ensure compliance with ethical norms from the initial stages of system development.

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Transparency is another essential aspect, particularly in ensuring that users, such as educators, always know whether they are interacting with a machine or a human. This is particularly relevant for educators and school staff using AI tools like those in the **stAI project**. Ensuring transparency about AI capabilities and limitations fosters trust and informed decision-making as reliable communication about AI capabilities and limitations fosters trust and informed use, which is crucial for projects like **stAI** and similar initiatives.

Furthermore, the **long-term implications of AI** use in education must be carefully considered, including how data is stored and how decisions impact children over time. **Risk and impact assessments** should consider direct and indirect effects on all stakeholders to identify and mitigate potential negative consequences for children, such as psychological impacts or algorithmic biases.

These ethical considerations align with the **European Declaration on Digital Rights and Principles**[19], which reinforces the need for AI systems to respect human rights, promote informed digital interactions, and safeguard individual autonomy. Among its commitments, the declaration emphasizes the importance of ensuring that AI systems are human-centric, transparent, and based on unbiased data. It also underscores the need to prevent AI from preempting personal choices, particularly in critical domains such as **education**, health, and private life. Research and development in AI must adhere to the highest ethical standards and comply with EU laws.

The **EU guidelines** stress the importance of avoiding **unfair bias in AI systems.** Biases can stem from historical inaccuracies, data incompleteness, or flawed governance models. These biases may lead to unintended discrimination or prejudice against certain groups, exacerbating marginalization. Additionally, harm can result from the intentional exploitation of biases, such as through unfair competition or price manipulation in a non-transparent market.

To mitigate these risks:

- **Bias in Data Collection**: Discriminatory biases should be identified and removed during the data collection phase wherever possible.

[19] https://digital-strategy.ec.europa.eu/en/policies/digital-principles

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- **Bias in Algorithm Design**: Oversight processes should be implemented to ensure transparency in the system's purpose, constraints, requirements, and decisions.

Under the **Trustworthy AI Assessment List**, specifically the section on **Diversity, Non-Discrimination, and Fairness**, developers are encouraged to:

1. Establish strategies or procedures to prevent the creation or reinforcement of unfair biases in both data usage and algorithm design.
2. Assess and acknowledge potential limitations arising from the composition of datasets.
3. Ensure diversity and representativeness of users within the datasets.
4. Test for biases within specific populations or problematic use cases.
5. Use available technical tools to enhance understanding of the data, model, and system performance.

Encouraging diverse hiring practices across backgrounds, cultures, and disciplines is also recommended to foster diverse perspectives during development.

In the context of education and projects like **stAI**, the ethical deployment of AI requires balancing innovation with safeguards for privacy, equity, and human rights. By adhering to EU guidelines, embedding ethics into AI design, and addressing long-term concerns, AI can significantly contribute to reducing ELET while respecting the rights and dignity of all stakeholders.

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4. Conclusion

The challenges associated with Early Leaving from Education and Training (ELET) require a unified effort from educators, policymakers, and technology developers. This handbook has explored both traditional approaches and AI-powered strategies for addressing the issue of ELET, with a focus on early identification, enhancing the school environment, and integrating innovative tools to support student well-being.

4.1 Summary of Key Recommendations

A major emphasis has been placed on the importance of early identification and intervention. Traditional methods, such as tracking attendance, monitoring behavior, and evaluating academic performance, continue to be crucial in predicting which students are at risk of dropping out. These approaches, have long been foundational in preventing ELET. However, the introduction of AI-powered tools, brings new possibilities. AI systems, capable of analyzing large amounts of data, offer more precise and real-time identification of at-risk students by uncovering patterns that may not be easily observable through traditional means. Predictive analytics and machine learning models are particularly effective in flagging early warning signs, enabling faster and more targeted interventions.

In terms of improving the school environment and enhancing student well-being, traditional strategies have always centered on creating supportive relationships, fostering an inclusive culture, and involving parents more closely in students' education. Octav Bancila has underscored these timeless approaches as key to maintaining a positive school climate where students feel safe, valued, and motivated. But today, AI can augment these efforts. AI-driven solutions, such as personalized learning platforms and mental health monitoring applications, cater to individual student needs in real time. These tools ensure that students not only receive tailored academic support but also benefit from timely interventions that address their emotional and psychological well-being.

When it comes to implementation strategies, the focus must be on effectively integrating AI into existing educational frameworks. The success of this integration hinges on structured, methodical planning. This includes training educators to use AI tools, securing buy-in from key stakeholders, and setting clear implementation steps that ensure smooth transitions. Furthermore, ethical considerations must be at the forefront of AI usage in education. It has been pointed out that the use of AI must be transparent, fair, and equitable, ensuring it doesn’t reinforce biases or deepen educational inequalities. AI should be leveraged as a tool to create more inclusive educational environments, not exacerbate existing disparities.

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4.2 Call to Action

The issue of ELET demands immediate and decisive action. All stakeholders—educators, school administrators, policymakers, and technology experts—must embrace both traditional and AI-powered strategies to improve educational outcomes. Policymakers must prioritize investment in AI technologies for schools, while educators need access to ongoing professional development to use these technologies effectively. Ethical frameworks must also be put in place to ensure AI is used in a way that supports all students, regardless of their background or circumstances.

Reducing ELET is within our grasp if we act now. By combining tried-and-true educational practices with cutting-edge technology, we can create more resilient and supportive school systems where every student has the opportunity to succeed. The time is now to embrace these innovations and build an educational landscape that leaves no student behind.

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References

1. Abd-Alrazaq, A., Alajlani, M., Ahmad, R., AlSaad, R., Aziz, S., Ahmed, A., … Sheikh, J. (2024). The Performance of Wearable AI in Detecting Stress Among Students: Systematic Review and Meta-Analysis. *Journal of Medical Internet Research*, 26(1). https://doi.org/10.2196/52622
2. Alexios-Fotios A. Mentis, Lee, D., & Roussos, P. (2024). Applications of artificial intelligence−machine learning for detection of stress: a critical overview. *Molecular Psychiatry*, 29, 1882–1894.
3. Anwar, A., Rehman, I. U., Nasralla, M. M., Khattak, S. B. A., & Khilji, N. (2023). Emotions Matter: A Systematic Review and Meta-Analysis of the Detection and Classification of Students' Emotions in STEM during Online Learning. *Education Sciences*, 13(9). https://doi.org/10.3390/educsci13090914
4. Azizah, Z., Ohyama, T., Zhao, X., Ohkawa, Y., & Mitsuishi, T. (2024). Predicting at-risk students in the early stage of a blended learning course via machine learning using limited data. *Computers and Education: Artificial Intelligence*, 7(June), 100261. https://doi.org/10.1016/j.caeai.2024.100261
5. Baneres, D., Rodriguez-Gonzalez, M. E., & Guerrero-Roldan, A. E. (2023). A Real-Time Predictive Model for Identifying Course Dropout in Online Higher Education. *IEEE Transactions on Learning Technologies*, 16(4), 484–499. https://doi.org/10.1109/TLT.2023.3267275
6. Bañeres, D., Rodríguez-González, M. E., Guerrero-Roldán, A. E., & Cortadas, P. (2023). An early warning system to identify and intervene online dropout learners. *International Journal of Educational Technology in Higher Education*, 20(1). https://doi.org/10.1186/s41239-022-00371-5
7. Brand C, E. J., Gabriel Ramirez, V. M., Diaz, J., & Moreira, F. (2024). Toward Educational Sustainability: An AI System for Identifying and Preventing Student Dropout. *Revista Iberoamericana de Tecnologias Del Aprendizaje*, 19, 100–110. https://doi.org/10.1109/RITA.2024.3381850
8. Chao Du, C. L., Balamurugan, P., & Selvaraj, P. (2021). Deep Learning-based Mental Health Monitoring Scheme for College Students Using Convolutional Neural Network. *International Journal on Artificial Intelligence Tools*, 30(06n08).
9. Ciolacu, M., Tehrani, A. F., Binder, L., & Svasta, P. M. (2018). Education 4.0 - Artificial Intelligence assisted Higher Education: Early recognition System with Machine Learning to support Students' Success. 2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME), (MI), 234–238. IEEE.
10. Dharmalingam, R., Baskar, S., & Ataullah, S. T. (2023). A Framework for Predicting the Students at Risk Using AI: A Case Study. Proceedings - Frontiers in Education Conference, FIE, 1–5. https://doi.org/10.1109/FIE58773.2023.10343232
11. Embarak, O. H., & Hawarna, S. (2024). Enhancing Student Success with XAI-Powered RADAR: An Automated AI-driven System for Early Detection of At-risk Students. *Procedia Computer Science*, 231(2023), 151–160. https://doi.org/10.1016/j.procs.2023.12.187
12. Gedam, S., & Paul, S. (2021). A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques. IEEE Access, 9, 84045–84066. https://doi.org/10.1109/ACCESS.2021.3085502
13. Joshi, M. L., & Kanoongo, N. (2022). Depression detection using emotional artificial intelligence and machine learning: A closer review. *Materials Today: Proceedings*, 58, 217–226. https://doi.org/10.1016/j.matpr.2022.01.467
14. Khare, S. K., Blanes-Vidal, V., Nadimi, E. S., & Acharya, U. R. (2024). Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations. *Information Fusion*, 102(September 2023), 102019. https://doi.org/10.1016/j.inffus.2023.102019
15. Kim, Y., Soyata, T., & Behnagh, R. F. (2018). Towards Emotionally Aware AI Smart Classroom: Current Issues and Directions for Engineering and Education. *IEEE Access*, 6, 5308–5331. https://doi.org/10.1109/ACCESS.2018.2791861
16. Liu, J., & Wang, H. (2022). Analysis of Educational Mental Health and Emotion Based on Deep Learning and Computational Intelligence Optimization. *Frontiers in Psychology*, 13(June), 1–7. https://doi.org/10.3389/fpsyg.2022.898609
17. Liu, S., Zhang, Y., Zhao, L., & Liu, Z. (2024). Academic stress detection based on multisource data: a systematic review from 2012 to 2024. Interactive Learning Environments, 1–27. https://doi.org/https://doi.org/10.1080/10494820.2024.2387744

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18. Marengo, A. Pagano, A. Pange, J. & Soomro, K.A. (2023). The educational value of artificial intelligence in higher education: a ten-year systematic literature review. *Interactive Technology and Smart Education*, 21(4), 625-644. https://doi.org/10.20944/preprints202311.0055.v1
19. Mahligawati, F., Allanas, E., Butarbutar, M.H. & Nordin N.A.N. (2023). Artificial intelligence in physics education: a comprehensive literature review. *Journal of Physics Conference Series*, 2596(1). https://doi.org/10.1088/1742-6596/2596/1/012080
20. Mittal, U. Sai, S., Chamola V. & Sangwan, D. (2024). A Comprehensive Review on Generative AI for Education. *IEEE Access*, 12, 142733-142759. https://doi.org/10.1109/ACCESS.2024.3468368
21. Nie, J., & Ahmadi Dehrashid, H. (2024). Evaluation of student failure in higher education by an innovative strategy of fuzzy system combined optimization algorithms and AI. Heliyon, 10(7), e29182. https://doi.org/10.1016/j.heliyon.2024.e29182
22. Panda, M., Sharma, A., & Jaiswal, G. (2024). Cognitive Wellness Assessment: A Comprehensive Review of Deep Learning and Machine Learning Approaches for Mental Stress Detection in the Digital Age. Proceedings of the 14th International Conference on Cloud Computing, Data Science and Engineering, Confluence 2024, 668–673. https://doi.org/10.1109/Confluence60223.2024.10463296
23. Pek, R. Z., Ozyer, S. T., Elhage, T., Ozyer, T., & Alhajj, R. (2023). The Role of Machine Learning in Identifying Students At-Risk and Minimizing Failure. IEEE Access, 11, 1224–1243. https://doi.org/10.1109/ACCESS.2022.3232984
24. QuadC. 20th of February.
25. Roshanaei, M., Olivares, H. & Lopez, R.R. (2023). Harnessing AI to foster equity in education: opportunities, challenges, and emerging strategies. *Journal of Intelligent Learning Systems and Applications*, 15(04), 123-143. https://doi.org/10.4236/jilsa.2023.154009
26. Schleiss, J., Laupichler, M.C., Rapuach, T. & Stober, S. (2023). AI course design planning framework: developing domain-specific ai education courses. *Education Sciences*, 13(9), 954. https://doi.org/10.3390/educsci13090954
27. Shoaib, M., Sayed, N., Singh, J., Shafi, J., Khan, S., & Ali, F. (2024). AI student success predictor: Enhancing personalized learning in campus management systems. *Computers in Human Behavior*, 158(May), 108301. https://doi.org/10.1016/j.chb.2024.108301
28. Singh, M., Bharti, S., Kaur, H., Arora, V., Saini, M., Kaur, M., & Singh, J. (2022). A Facial and Vocal Expression Based Comprehensive Framework for Real-Time Student Stress Monitoring in an IoT-Fog-Cloud Environment. IEEE Access, 10, 63177–63188. https://doi.org/10.1109/ACCESS.2022.3183077
29. Tiwari, S., & Agarwal, S. (2021). A Shrewd Artificial Neural Network-Based Hybrid Model for Pervasive Stress Detection of Students Using Galvanic Skin Response and Electrocardiogram Signals. Big Data, 9(6). https://doi.org/https://doi.org/10.1089/big.2020.0256
30. Ujkani, B., Minkovska, D., & Hinov, N. (2024). Course Success Prediction and Early Identification of At-Risk Students Using Explainable Artificial Intelligence. Electronics (Switzerland), 13(21), 1–24. https://doi.org/10.3390/electronics13214157
31. Vistorte, A. O. R., Deroncele-Acosta, A., Ayala, J. L. M., Barrasa, A., López-Granero, C., & Martí-González, M. (2024). Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review. *Frontiers in Psychology*, 15(June). https://doi.org/10.3389/fpsyg.2024.1387089
32. Zhao, H. (2024). Psychological Health Assessment and Intervention System for Chemical Engineering Students Based on Emotional Computing Technology. *Journal of Electrical Systems*, 20(3s), 1874–1885. https://doi.org/10.52783/jes.1727

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