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# The Role of Predictive and Generative AI in Shaping Modern Education: Current Applications and Opportunities

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# The Role of Predictive and Generative AI in Shaping Modern Education: Current Applications

## Introduction

AI in education (AIEd) has been researched for over 30 years, with the International AIEd Society (IAIED) founded in 1997 to advance the field [1]. The term "artificial intelligence (AI)" was coined by John McCarthy in 1956 during the Dartmouth Conference, marking the formal beginning of AI as a field [1]. Machine learning (ML) is a subset of AI that enhances its ability to optimize operations and provide real-time responses. It enables computers to act, think, learn, and operate independently within the broader AI framework [2]. Within this framework, generative AI represents a further advancement, focusing on creating new data and content, thus expanding the capabilities and applications of machine learning in various domains. The evolution of AI in education has been transformative, significantly altering both how students learn and how educators teach.

Predictive AI in education forecasts student outcomes and clusters students, identifying risks and enabling targeted interventions. Predictive AI studies utilize a diverse range of data features in machine learning models. This may include leveraging features from demographic and transcript data [3], behavioral data from Learning Management Systems (LMS) [4], and other sources to generate insights that support both students and educators. The goal of predictive AI in higher education is to enhance student outcomes by providing actionable insights into academic performance, identifying potential risks, and personalizing learning experiences. This type of prediction can be performed with supervised or unsupervised models, at the degree level, course level, or individual level, with varying input data, implementation, and goals. Generally, research in this field is motivated by the high rates of college students dropping out before finishing their degree [3], the growing percentage of students taking longer than 4 years to complete their Bachelor's degree [3, 5], and the growing implementation of online courses which typically have higher attrition rates [6].

Generative AI (GenAI) focuses on creating new content, such as text, images, and music [7], using deep learning models like GANs and transformers to generate original data by learning patterns from training datasets. Unlike traditional machine learning, which primarily analyzes or classifies existing data [8], GenAI models, such as OpenAI's GPT, leverage large language models (LLMs) trained on vast text datasets [9, 10]. Beyond LLMs, models like GANs, VAEs, and diffusion models further expand GenAI's capabilities, with applications spanning NLP [11], art creation [12], and game design [13]. The release of ChatGPT quickly raised concerns about academic integrity and student overreliance, potentially hindering learning due to its accessibility [14, 15]. However, these concerns have also driven interest in leveraging GenAI to enhance education. Studies show that students benefit from using ChatGPT in the classroom [16, 17], and many educators now view AI as a valuable tool for enriching learning experiences for both students [18, 19] and teachers [20, 21].

## Project Approach

### *Research Categorization Framework*

Figure 1, below, gives an overview of what will be covered within this work. AI is broken down into (i) Predictive AI and (ii) Generative AI. These topics are further categorized by (a) learning type and architecture and (b) application level and focus, which will be explained in detail below. Although some aspects of the categorization may be subjective, it primarily serves as a framework for organizing the research and highlighting trends within each category.

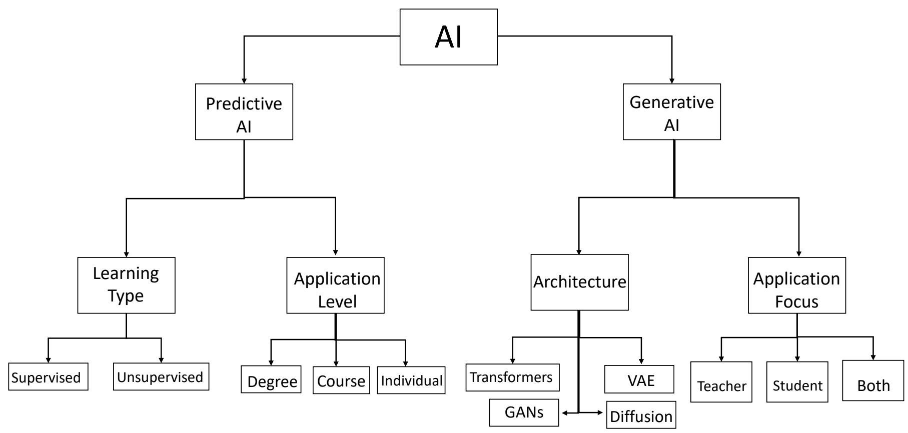


**Figure 1: Overview of categories associated with predictive and generative AI discussed in this work text.**

The method of categorization used within this work was developed in the process of conducting this research, evolving in response to the data collected and the specific analytical needs that emerged. An initial review of numerous studies on predictive AI in education revealed a recurring pattern in research objectives and implementations. Typically, predictive models were designed to forecast student failure [22, 23] (**Course Level**) or dropout [24, 25] (**Degree Level**). However, some studies adopted a more personalized approach, incorporating student-specific goals or utilizing more individualized data than what was commonly used in course- or degree-focused research [26, 27] (**Individual Level**). To simplify the analysis, Learning Type was limited to **Supervised** and **Unsupervised** approaches, excluding Semi-Supervised and Hybrid methods.

The use of generative AI in education is much newer than predictive AI. As it continues to develop, significantly fewer studies have explored its application in classroom teaching. Moreover, the objectives of these studies differ substantially from those of predictive AI. Rather than forecasting student success, generative AI aims to enhance the learning experience. However, its impact extends beyond students to include teachers as well. This is evident from the growing body of research on teacher and student perceptions of generative AI in the classroom [28, 29, 30]. For this reason, studies were analyzed through the lens of **Student-Focused** or **Teacher-Focused** implementations of generative AI in education. After the analysis began, it became evident that some studies on generative AI in education did not have a clearly defined primary beneficiary. To account for this, a third category (**Both**) was introduced. This category includes research that provides equal benefits to both teachers and students. For example, studies that use generative AI to generate personalized feedback (beyond just a numerical grade) reduce teachers' workload while also offering students tailored insights to improve their assignments. In terms of architecture, most studies on generative AI in education currently focus on ChatGPT and similar tools (**Transformer**). While the other selected architecture categories (**GAN**, **VAE**, **Diffusion**) are not exhaustive, they were chosen based on the presence of existing research within those areas. Beyond Transformers, there is a notable lack of studies exploring other generative AI architectures in educational contexts.

While some studies provide an overview or analysis of predictive AI implementations in education [31, 32, 33], none specifically examine the patterns within the categories discussed in this paper. Even fewer studies explore the implementation of generative AI in educational settings [34, 35]. Many focus on the potential implications of generative AI rather than analyzing studies that have tested its application in real classroom environments. This paper aims to identify current trends in the use of predictive AI and generative AI in education by examining their application across specific domains. For predictive AI, the focus is on its implementation at different levels—degree, course, and individual. For generative AI, the analysis considers its role in student-centered, teacher-centered, or dual-purpose applications.

### ***Predictive AI - Level of Application***

#### Degree Level

At the degree level, supervised models focus on predicting student persistence or dropout, while unsupervised models group students based on factors like performance, dropout risk, or study duration. These models rely on registrar data, including basic demographics, academic history, and long-term academic trends, This data provides broad insights rather than personalized details. By analyzing these broad patterns, institutions can pinpoint risk factors and implement strategic, long-term interventions to enhance student retention and graduation rates.

#### Course Level

At the course level, predictive models target immediate academic outcomes. Supervised models predict passing, failing, or achieving specific grades, while unsupervised models reveal patterns in engagement and learning behaviors, such as clustering by demographics, online activity, or risk of poor performance. These models use historical academic data combined with real-time LMS inputs, including login frequency, discussion participation, assignment time, and quiz or exam results. By continuously updating in real time, course-level models enable educators to quickly identify students who are struggling and implement timely interventions, such as offering additional tutoring or customized learning resources.

#### Individual Level

At the individual level, predictive models leverage detailed personal data to tailor support and address each student's unique needs. These models analyze inputs such as self-reported preferences, reflections, and biometric data to forecast academic performance, engagement, or learning styles. By prioritizing individualized strategies, predictive AI at this level empowers educators to address the specific challenges and strengths of each learner, fostering a more personalized and effective approach to education.

Figure 2, shown below, provides an overview of the common goals and input data used in predictive AI applications within education research.

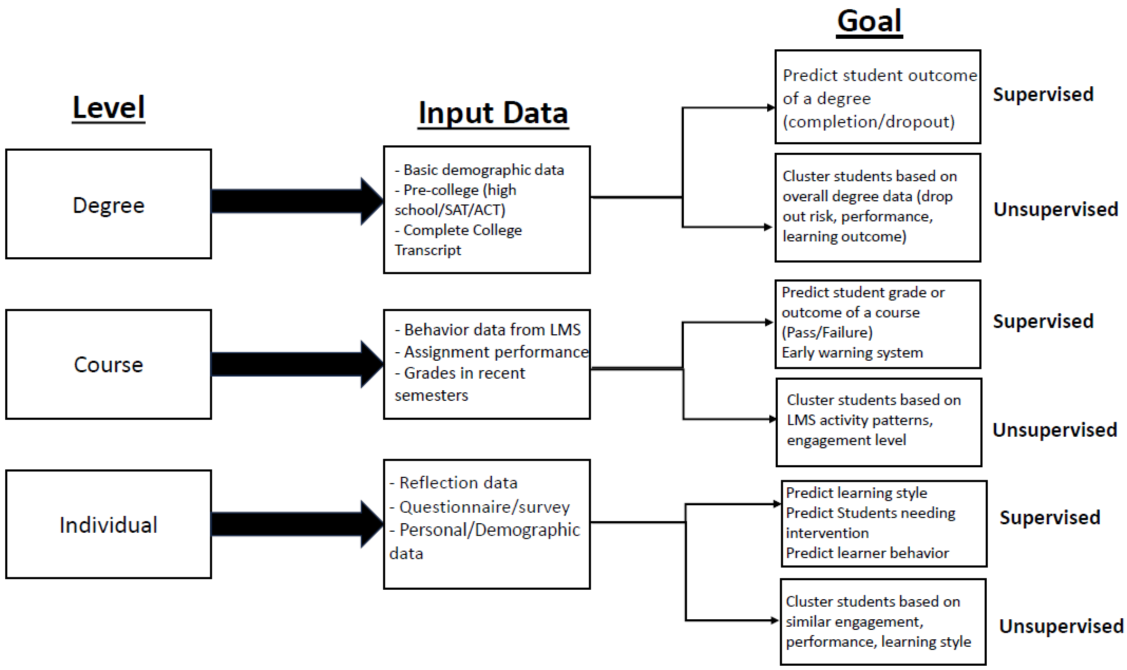


**Figure 2. Overview of input data and objectives across application levels of predictive AI in education contexts.**

*Predictive AI -Learning Type*

Supervised Learning

Supervised models in predictive AI are trained on datasets with input-output pairs, where the model learns relationships between inputs and labels [36]. These models are used for classification and regression tasks. Their success depends on high-quality labeled data and performs best with large, representative datasets [37]. Supervised learning has numerous applications in higher education, benefiting both students and teachers. It predicts enrollment patterns [38], helping universities optimize class sizes and resources, and enhances personalized learning by recommending courses based on performance and interests [39, 40]. It identifies at-risk students through historical data analysis—grades, attendance, and engagement with LMS—to detect early warning signs like poor performance or low participation. These interventions have proven to reduce dropout rates by addressing issues before they become insurmountable.

### Unsupervised Learning

Unsupervised learning, rooted in machine learning and statistics, emerged to address the reliance on labeled datasets in supervised learning [41]. Unsupervised machine learning focuses on analyzing unlabeled data, identifying patterns without predefined outputs [42]. Unsupervised learning in education is used to group students by factors such as engagement and learning behavior [43, 44, 45], academic performance and outcomes [46, 47], student reflections [48], and behavioral states [49]. While not predicting success directly, these methods guide personalized teaching strategies and targeted interventions.

## *Generative AI - Focus of Application*

### Student-Focused Applications

Despite concerns about the impact of ChatGPT on student learning, generative AI offers valuable opportunities in academia, including personalized learning paths [50, 51], peer collaboration [52], and additional tutoring support beyond classroom hours [53]. Leveraging these capabilities can create more dynamic and engaging educational environments while addressing potential challenges responsibly. However, fostering AI literacy is essential to ensure students become informed users. Understanding generative AI's mechanisms, biases, and limitations enables critical evaluation of AI-generated content—a crucial skill as misinformation continues to spread online.

### Teacher-Focused Applications

While most research on ChatGPT, and other generative models, emphasizes its impact on and support for students, there is significant potential for generative AI to alleviate workload and enhance various aspects of teaching for educators [54, 55, 56]. Generative AI can transform traditional teaching methodologies by helping teachers streamline administrative tasks [57], improve grading processes [55], and create tailored educational content [54]. Generative AI has proven to be a valuable asset in generating educational content for classes [58]. Additionally, generative AI can significantly improve the grading process and in turn, reduce teacher workload [59, 60, 61, 62].

## *Generative AI - Model Architecture*

### Transformers

A transformer model [63] is a type of deep learning architecture designed for handling sequential data, like text, without relying on recurrent connections. Transformers were developed to overcome the limitations of earlier models like RNNs and CNNs, particularly in handling long-range dependencies, vanishing or exploding gradients, and the slow training caused by sequential data processing. The generative capabilities of transformers are exemplified in models like GPT (Generative Pre-trained Transformer) [9] and its successors, which are capable of producing coherent, contextually aware text by predicting the next word in a sequence. These abilities extend beyond text to multimodal contexts, such as generating images from text prompts (e.g., DALL-E [64]) or synthesizing audio and code, illustrating the model's versatility.

Variational Autoencoders

The VAE structure enhances standard Autoencoders by addressing the non-regularized latent space issue and providing generative capabilities by having the encoder output parameters of a predefined distribution, which is constrained to a normal distribution to ensure a structured latent space [65]. This allows VAEs to generate new data samples by sampling from the learned latent space, whereas traditional Autoencoders primarily focus on reconstructing input data without generating new examples. VAEs play a valuable role in educational research by learning efficient feature embeddings [66, 67], assisting with feature extraction [68], and mining insights from educational questions [69].

Generative Adversarial Networks (GANs)

GANs were first introduced by Goodfellow [70] in 2014 as a novel approach to generative modeling. This framework revolutionized generative models and has since been applied across various fields, from image synthesis to data augmentation and beyond. In educational contexts, GANs have primarily been leveraged for synthetic data generation [71, 72, 73], a technique aimed at enhancing predictive models for student outcomes. Despite their success in other fields, GANs have been less explored in education research compared to their potential, though not as much as Diffusion models and VAEs, which remain largely absent from educational contexts.

Diffusion Models

Diffusion models are a class of generative models that work by gradually transforming noise into structured, high-quality outputs through a multi-step denoising process [74]. As adaptable foundation models, they excel in tasks like image denoising and generation but may operate more slowly due to their reverse sampling process [75]. As a result, they are highly effective for applications such as image generation, super-resolution, and denoising. A prominent example of diffusion models is Stable Diffusion, an open-source model developed by Stability AI in collaboration with the CompVis group at Ludwig Maximilian University of Munich [76]. The key distinction of this model compared to others is its use of a latent diffusion model, allowing it to modify images by performing operations within its latent space [76].

## Results and Discussion

*Examples of Predictive Models Across Application Levels in the Context of Education*

The table below presents a collection of references, organized by the specific application level and the type of learning implemented. Each category is designed to illustrate how different predictive models are applied across various contexts in the field of education. To offer a more comprehensive understanding, trends and several representative examples from each category are discussed in the following sections.

**Table 1. Relevant references according to application level and learning type of predictive AI applications.**

| Application Level | Learning Type | References |
|---|---|---|
| Degree | Supervised | [5, 24, 25, 77, 78, 79, 80] |
| Course | Supervised | [22, 81, 23, 82, 83, 84, 85, 86, 87, 88] |
| Individual | Supervised | [89, 26, 27, 90, 91, 92] |
| Degree | Unsupervised | [93, 46, 94, 47, 95] |
| Course | Unsupervised | [96, 97, 98, 99, 100] |
| Individual | Unsupervised | [48, 101, 43, 49, 102, 103, 89, 104, 105] |

Supervised Models

The referenced applications in the supervised learning categories cover a range of implementations, including predicting student grades [22, 81, 83], predicting degree performance [24, 25, 80, 106], predicting learning style [91, 89], identifying students at risk of dropping out of courses [23, 82, 83], monitoring student behavior in class [84], and providing personalized interventions [26].

***Degree Level.*** At the degree level, the goal of predictive machine learning in education is often to identify students at risk of dropping out. By analyzing factors like academic performance, attendance, and engagement, these models aim to flag at-risk students early, allowing for timely interventions to improve retention and support student success.

At this level, student data often includes high school grades [24, 77, 106, 5], sometimes alongside SAT, ACT, university admission test scores, or similar standardized assessments [24, 106]. Some studies also incorporate demographic factors such as ethnicity and gender [78, 77, 79, 80, 5]. Unlike course-level analyses, current semester performance is not considered; instead, past semester performance is used [24]. In some cases, current enrollment data is included [79, 78, 80], as it helps gauge semester difficulty and contributes to dropout predictions.

Almost all examples, within the table, at the degree level use Random forest as one of the prediction models [24, 25, 77, 79]. SVM is also a very common model for dropout prediction [25, 77], as well as Decision tree and neural networks [79].

***Course Level.*** At the course level, predictive machine learning in education often focuses on forecasting student grades or identifying those at risk of failing. These models analyze coursework data, engagement metrics, and assessment results to predict performance, enabling targeted support and early interventions to help students succeed.

In terms of data at this level, it's very common that data from an LMS is used [22, 83, 85, 86]. An LMS is a software application that facilitates the administration, documentation, tracking, reporting, and delivery of educational courses. The data collected from an LMS can include a variety of metrics such as student login frequencies, participation in discussion forums, assignment submission rates, quiz and exam scores, and overall course completion rates. This type of data gives a more real-time look at academic performance and engagement. Even if data isn't gathered from an LMS, studies at this level almost always include some sort of academic performance data like recent assignment grades [85, 83]. Sometimes data indicating performance in prior semesters is used [87]. At this level, additional personal data is often collected through surveys, supplementing what is typically available from the registrar [81, 83, 88].

With regard to predictive models, Random forest is also very common at this level [86, 87, 85, 83, 81], as well as KNN [81, 23, 83] and SVM [87, 86, 85, 83, 81]. The use of neural networks is more prevalent at this level than at the degree level [84, 85, 23, 82, 86, 22, 88], including architectures such as MLPs (Multi-Layer Perceptrons), LSTMs (Long Short-Term Memory networks), and CNNs (Convolutional Neural Networks), and other types of deep neural networks.

***Individual Level.*** At the individual level, predictive machine learning in education often focuses on personalizing learning experiences by predicting students' learning styles or preferences. By analyzing survey data, past interactions, and behavioral patterns, these models offer more effective insights into student engagement and performance, allowing educators to tailor teaching methods and resources to each student's unique needs for a more inclusive learning environment.

At the individual level, studies implementing supervised learning use a wide variety of data. This can include data from surveys [90], user comments or conversations [26, 105], LMS data [89, 91], or even sensor-based data such as facial recognition, EEG readings, or heart rate measurements [92, 104]. A key trend is that the data tends to be increasingly personal; even when the data itself is not inherently individual, the goal of the prediction often focuses on personal aspects, such as learning style or behavior.

At this level, neural network models such as CNN, RNNs (Recurrent Neural Networks), and BPNNs (Backpropagation Neural Networks) [92, 26, 91, 89] are more likely to be used, while traditional models are less commonly applied. Research that does use traditional models at this level tends to favor decision trees more frequently compared to other levels [104, 105, 89].

### Unsupervised Models

The referenced applications within the unsupervised learning categories include a variety of implementations, such as clustering students into dropout risk levels [46], clustering student performance features or levels [94, 47], grouping students by learning outcomes [95], clustering student reflections [48], clustering learner behavior [98, 97, 43, 49, 99], and identifying topic weaknesses for specific students through clustering [102].

***Degree Level.*** The degree-level studies using unsupervised models, as indicated in the table, draw on diverse data sources, including pre-admission indicators, psychological assessments, academic records, co-curricular and extracurricular activities, and senior exit surveys. Compared to supervised models at the same level, these studies often use more personal data. However, the assessments and surveys are typically administered to all students either before graduation or during enrollment. While some studies incorporate academic data [94, 93], many also include survey or assessment responses [95, 46], co-curricular activities [47], awards [47], and residential location information [94].

The goals of the indicated references are extremely varied, including grouping university students based on their level of dropout risk [46], predicting the classification of degrees students graduate with (e.g., first class, second class upper, second class lower, third class, or pass) based on their CGPA [94], clustering students according to their academic performance [47], clustering students based on learning outcomes from their degree [95], and identifying homogeneous groups of students by combining academic performance with the length of their bachelor's program [93].

Most of these studies use K-Means clustering [46, 94, 47, 93], but other models are also employed, including density-based algorithms like DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) [46], self-organizing maps (SOM) [94], BIRCH (Balanced Iterative Reducing and Clustering Using Hierarchies) [47], and bottom-up hierarchical clustering using Euclidean distance measured via a Proximity Matrix [95].

***Course Level.*** All of the references indicated at the course level that use unsupervised learning incorporate some type of LMS data [96, 98, 100, 97, 99], which is similar to the data used in supervised models at the course level. One study also incorporates demographic characteristics [96].

The goals of the indicated references at the course level tend to focus on measuring engagement and performance of students in the course based on LMS data. Goals include identifying how demographic characteristics of students and their engagement in online learning activities affect their learning achievement [96], identifying clusters of learners with similar online temporal behavior [98], clustering students based on their engagement with course materials [99], analyzing virtual learning engagement [100] and identify clusters of students at risk of unsuccessful learning outcomes [97].

Similar to the degree-level studies using unsupervised models, most of these course-level studies use K-Means [96, 99, 100, 97]; however, other models are also employed, including graph-based clustering [98], DBSCAN [100], hierarchical clustering [100, 97], and affinity propagation algorithms [100].

***Individual Level.*** The data used in studies at the individual level with unsupervised models, as indicated in the table, includes reflections from a software engineering course [48], head pose, keystrokes, and action logs from tutoring systems [43], behavioral data from students on campus [49], assignment performance [102], questionnaire responses [103], and wearable sensor data, such as electrodermal activity and heart rate variability [101]. This dataset variety exceeds that of supervised models at any level or other levels of unsupervised model implementation.

The goals of studies indicated in the table that use unsupervised models at the individual level include clustering student reflections to streamline reading while preserving content understanding [48], identifying distinct engagement states (e.g., engaged, starting out, disengaged) [43], clustering of student behavioral patterns based on real-time behavior [49], analyzing topic weaknesses [102], grouping students by common traits in questionnaire responses [103], and exploring autonomic responses to medical simulation training [101].

Similar to the other levels that use unsupervised models, the individual level also largely utilizes the K-Means model [48, 49, 102, 103, 101]. Other models used include the unsupervised learning mode of Hidden Markov Models (HMM) [43], DBSCAN [49], and hierarchical clustering [103].

*Examples of Generative Model Application by Focus in the Context of Education*

The table below presents a collection of references, organized based on the specific focus of the application and the type of model architecture employed. Each category is structured to highlight how different generative models are applied to various contexts within the scope of education. To provide a deeper understanding, a few representative examples from each category are elaborated on below.

**Table 2. Relevant references according to application focus and model architecture of generative AI applications.**

| Model Architecture | Application Focus | References |
|---|---|---|
| Transformer | Student-Focused Application | [107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 54] |
| Transformer | Both | [117, 118, 59, 60, 61, 62, 119, 120] |
| VAE | Teacher-Focused Application | [121, 122] |
| VAE | Student-Focused Application | [123, 124] |
| GAN | Teacher-Focused Application | [71, 72, 73, 125, 126, 127] |
| GAN | Student-Focused Application | [128, 129] |
| Diffusion | Teacher-Focused Application | [130] |
| Diffusion | Student-Focused Application | [131, 132, 133] |

Transformers

The applications of the references outlined above in the transformer categories encompass a variety of implementations that fall into one of the following categories: providing simulations [112, 113], offering tools for personalized learning [54], generating feedback [59, 60, 61, 62, 119], enhancing assessment [134, 55, 56], creating educational content [135, 136, 118], a tutoring system or chatbots that provides assistance to students [109, 107, 110, 111, 114, 117, 120], and integrating AI into courses as part of assignments [108, 115, 116].

***Teacher-Focused.*** The teacher-focused applications of transformer-based generative AI, indicated above, primarily aim to reduce teacher workload by automating tasks such as assessment and the creation of teaching materials. Additionally, some of the examples provide educators with insights and guidance on effectively integrating generative AI into their courses or inform them about the capabilities and limitations of GenAI.

Some key goals include streamlining assessment [134], particularly for evaluating text-based responses [55], and developing scalable guidelines for integrating AI assistance in classroom assessments [56]. Researchers have also explored LLM-generated learning resources, comparing their effectiveness to human-created materials [135], as well as AI-generated teaching videos versus human-made ones [136]. Additionally, generative AI is being used to help teachers integrate AI tools into creative problem-solving (CPS)-focused learning environments, enhancing instructional methods and teaching practices [137].

Of the references that provide input data or prompts to a model, some use student assignments [134, 55] and some prompt ChatGPT to generate code samples and explanations [135] or to create a lesson for a particular topic [136]. Additionally. several studies used some version of ChatGPT [136, 137, 134], but other studies used Codex [135] or created a customized tool that utilized GPT [55].

***Student-Focused.*** The student-focused applications described in the table emphasize the use of LLM-based tools as virtual teaching assistants to support student learning or assist students in completing assignments. These studies also evaluate the impact of LLM integration on student learning outcomes, while some examples involve the use of LLM-powered agents to create interactive classroom simulations.

The goals of the references highlighted in the table are highly varied. A key focus is on personalized learning [54] and enhancing programming education through LLM-integrated tutoring systems [107]. One study shifts a computer science course from syntax and code writing to software production with LLM assistance [108]. Other research explores undergraduate perceptions of GenAI tools [109] and their role in improving learning through customized support [110]. Another reference also highlights the impact on social cognition and learning in robotics-based education [111], including applications in Indonesian sociology programs. AI-driven simulated classrooms [112], such as MATHVC, the first LLM-powered virtual classroom [113], are also included. Additionally, GenAI is explored as a virtual teaching assistant [114] in specialized writing tasks like Can You Spot the AI [115] and in ChatGPT-assisted biochemistry assignments [116].

The studies utilized various types of input data and prompts, including lesson details such as the title, content, topics covered, and learning outcomes [54]. Other inputs included prompts used to generate programming functions [107], student questions or interactions [114, 110, 111], and interactions within the learning environment [112]. Data from middle school math assignment submissions were also analyzed [113]. As well as student provided prompts to generate a writing assignment [115].

Most of the studies used a version of ChatGPT [107, 112, 113, 114] or integrated the GPT model in some way [54, 109, 111]. Other models/applications that were used include: GitHub Copilot [108, 110], custom generative tools created for the course [110], and Bard or Bing AI [107, 110].

***Both.*** As mentioned earlier, some generative AI applications provide significant benefits to both teachers and students. For instance, automatic feedback generation can streamline the grading process for instructors while offering students timely and personalized feedback to enhance their learning experience.

LLM-based transformer models in education enhance learning by providing personalized, timely feedback. One approach evaluates the impact of LLM-generated feedback compared to no feedback on learning outcomes [59]. Other applications integrate GenAI in educational forums to assist instructors, analyze student communications [61], and monitor sentiment to boost engagement and inspire projects [60]. Additionally, GenAI tools support MOOC learners by analyzing educational data to improve understanding and performance [62]. These studies underscore the value of integrating GenAI for feedback, engagement, and skill development.

These studies utilized diverse data sources reflecting student engagement, performance, and linguistic progress. One dataset included over 12,000 Discord messages exchanged between students and instructors over four years, covering class discussions, assignment feedback, and general queries [60]. Another analyzed LMS data and assignment performance metrics, incorporating course progression, results, timestamps, and behavioral patterns [62]. Linguistic improvement was assessed through a pre-and post-test design with diagnostic writing tasks and weekly 300-word assignments [119]. Other studies relied on student questions [61] or assignments [59]. Notably, all references labeled BOTH in the table used a version of the GPT model.

Variational Autoencoders (VAE)

The applications of the references outlined above in the VAE categories encompass a variety of implementations that fall into one of the following categories: enhancing EWSs [121], detecting student actions [122], and teaching tools [123]. While Lyu is partly focused on a web-based game to introduce how VAEs work [124], this work also used a Google Colab notebook for students to retrain VAEs using their own hand-drawn examples to strengthen their understanding.

The applications of VAE models in education serve various purposes to enhance learning and teaching. One key use is generating synthetic at-risk samples to balance datasets for early warning systems [121]. VAEs also aid in student action recognition, helping educators monitor engagement in online courses [122]. Additionally, a web-based GUI leverages a neural-network-based VAE to guide interactive sketching [123]. Another example includes a web-based game using Plato's cave metaphor and a Google Colab notebook for retraining VAEs with hand-drawn digits, making VAE concepts more accessible [124].

The diverse goals of these studies result in varied data types. One application uses student behavioral data, discussion posts, and final grades to analyze engagement and performance [121]. Another processes video data of nine students performing seven actions, such as writing and using a smartphone, into image sequences for analysis [122]. A third leverages the QuickDraw dataset, which contains user-generated vector sketches from the "Quick, Draw!" game [123]. Each dataset offers unique opportunities for VAE models in educational research.

The models used in these applications include the custom LVAEPre model [121], which combines Ladder VAE (LVAE) and a Deep Neural Network (DNN). Another model used is the Adjusted VAE (AVAE) [122], a variation of the standard VAE. Additionally, the standard VAE model [124, 123] is also employed.

Despite identifying some initial applications of VAEs in the educational domain, the research in this area remains sparse. Given their robust capacity for learning complex data distributions and generating meaningful latent representations, VAEs present a promising opportunity for various educational tasks.

Generative Adversarial Networks (GAN)

The referenced applications within the VAE categories encompass a range of implementations that can be grouped into the following categories: including improving data quality or anonymizing student data for further analysis [71, 127], enhancing predictions of student outcomes [72, 73, 125], detecting student engagement [126], and developing educational tools [128, 129].

The references in the table highlight key applications of GANs in education. Many studies use GANs to generate synthetic data, addressing data sparsity and improving model reliability [71, 72, 127, 73, 125], while also mitigating privacy concerns. Other applications focus on personalized learning, such as adaptive educational games and tailored content [128]. Additionally, GANs enhance classroom analysis through facial expression recognition [126] and support self-directed learning with text-to-image storytelling [129].

GAN applications in education utilize diverse datasets to address various challenges. AutoTutor ARC data generate learner data for assessing ITS designs [71]. Farhood [72] creates synthetic student performance data using the Math dataset (395 real student records, 33 features) and the Exam dataset (1,000 fictional records, 8 features), both predicting pass/fail outcomes. Facial expression data from public datasets like Oulu-CASIA, CK+, and FMEO are used to analyze student engagement [126]. A survey-based dataset on university teachers' digital competence is expanded via COPULA-GAN [127]. Additionally, pre-built educational game levels support adaptive content generation [128]. These datasets showcase GANs' role in performance prediction, emotional analysis, and personalized learning.

The identified references showcase a diverse range of GAN models, including the standard GAN model [71], CopulaGAN and CTGAN (Conditional Tabular GAN) [72], CGAN (Conditional GAN) in combination with an SVM model [73], ICGAN (Interpretable Conditional GAN) in combination with an SVM model [125], an enhanced GAN with an auxiliary classifier layer [126], CopulaGAN in combination with a data analysis technique implemented in SPSS (Statistical Package for the Social Sciences) under the name of "two-stage cluster" [127], and DCGAN (Deep Convolutional GAN) [128]. Each is tailored to address specific educational challenges such as data augmentation, adaptive content generation, and enhanced predictive analytics.

Diffusion Models

The referenced applications within the diffusion model categories cover several areas, including personalized learning [132], visual arts education and artwork generation [130, 133], and teaching tools [131].

The identified references highlight key applications of diffusion models in education. One major focus is enhancing art and design education through text-to-image models like Stable Diffusion, enabling creative expression and teaching art concepts via natural language prompts [130]. Another application uses diffusion models for dance instruction, extracting rhythmic and emotional cues from audio to generate real-time dance sequences with virtual tutors [131]. Diffusion models also streamline the creation of personalized instructional videos, improving content efficiency [132]. Additionally, they democratize generative art tools for novice users, integrating tangible elements to create immersive learning experiences [133]. These applications demonstrate diffusion models' potential to enhance interactivity, personalization, and accessibility in education.

The input data for diffusion model applications in educational contexts varies significantly across the identified references. For text-to-image AI in art education, a large dataset comprising 72,980 Stable Diffusion prompts serves as the basis for exploring generative visual art creation [130]. In the domain of dance instruction, two major datasets are employed: the AIST++ dataset, the largest of its kind for 3D human dance motion, includes 1,408 sequences from 30 subjects across 10 dance genres, supporting tasks like motion prediction and pose estimation; and the FineDance dataset, which provides a comprehensive collection of music-dance pairs, covering a wide range of dance styles for synchronized motion generation [131]. In another example in art and design education, the input data consists of tangible building blocks, which students manipulate to create digital artwork, integrating physical elements with generative AI models to foster creativity and facilitate interdisciplinary learning [133].

The identified references utilize a range of diffusion models to support various educational applications. Central among them is Stable Diffusion [130, 133], which in one application is used in combination with an unsupervised learning model [130] and in another example is used in combination with ControlNet [133]. In another example [131] Denoising Diffusion Probabilistic Model (DDPM) was used and in Kumar [132], the authors have suggested using Stable Video Diffusion and Deforum Stable Diffusion software.

Despite the rapid advancement of diffusion models in various fields, their application in education remains limited. Current research primarily focuses on art and design tasks, with few studies exploring broader educational uses like personalized content creation or adaptive learning experiences.

*Conclusion*

This work has examined the current applications of predictive and generative AI in education. As AI continues to evolve rapidly, new technologies and methodologies create promising opportunities for both predictive and generative AI to further enhance learning and teaching. This study contributes to the field of Artificial Intelligence in Education (AIED) by identifying current trends in the application of predictive AI and generative AI within educational settings. By classifying predictive AI at different levels—degree, course, and individual—and generative AI by its application focus—student-centered, teacher-centered, or both—this research provides a structured framework for understanding how these technologies are currently used. This classification is essential for AIED because it offers a clear map of existing implementations, helping educators and researchers who wish to integrate predictive or generative AI into their classrooms make informed decisions. Additionally, by identifying gaps in current applications, this study highlights opportunities for further research and development, encouraging contributions that address unexplored areas or refine existing AI-driven educational practices. Ultimately, this work supports both practitioners seeking practical applications and researchers aiming to advance AI's role in education.

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