To What Extent Does AI-Precision Education Improve Student Learning Outcomes Compared to Traditional Instructional Methods

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This study explores the impact of AI-Precision education on student learning outcomes compared to traditional instructional methods. The analysis covers key metrics such as academic performance, engagement, retention, and satisfaction. The results show that students in the AI-Precision group outperformed their counterparts in the Traditional group, with 67.5% of AI-Precision students earning A grades, compared to 12.5% in Traditional education. AI-Precision students also demonstrated a higher mean grade of 92.44, as opposed to 75.89 for Traditional students. Additionally, engagement levels were markedly better in AI-Precision education, where no students were classified as "Not Engaged," while 48.75% of students in Traditional education fell into this category. Retention rates were similarly higher, with AI-Precision students achieving a mean retention score of 7.61 versus 4.50 in Traditional settings. In terms of satisfaction, both students and parents expressed a clear preference for AI-Precision education. The mean parental satisfaction rating (out of 5) was 4.08 for AI-Precision compared to 2.48 for Traditional education, and 80.41% of students rated AI-Precision between 6 and 10. These findings suggest that AI-personalized education is more effective at improving academic performance, fostering engagement, and enhancing overall satisfaction. While traditional methods demonstrate more varied outcomes, AI-Precision reduces the prevalence of lower performance and disengagement, positioning it as a more effective learning approach.

Key Words: AI-Precision Education, Student Learning Outcomes, Traditional Instructional Methods, Personalized Learning, Adaptive Learning, Behavioral Data, Engagement Metrics, Real-Time Feedback, Resource Utilization, Retention Rates, ANCOVA

Introduction

Background

Artificial Intelligence (AI) and machine learning technologies have significantly transformed various sectors, including education. Precision education, a concept parallel to precision medicine, aims to tailor educational experiences to individual learners' needs using advanced computational techniques. This shift from traditional, one-size-fits-all educational approach promises to enhance learning outcomes by addressing each student's unique requirements (Chen et al. 2023).

Problem Statement

Traditional instructional methods often fail to accommodate the diverse learning styles, paces, and needs of individual students. This limitation can lead to disengagement, poor performance, and higher dropout rates. AI-Precision education offers a potential solution by providing customized learning paths and real-time feedback, thereby improving student engagement and learning outcomes. (Zhang 2023).

Significance of Study

This study explores the extent to which AI-Precision education can improve student learning outcomes compared to traditional instructional methods. By systematically reviewing empirical studies and analyzing survey data, this research aims to provide insights into the effectiveness, challenges, and future directions of AI-Precision education.

Literature Review

Introduction to AI-Precision Education

AI-Precision education utilizes machine learning algorithms to analyze students' data and create customized learning experiences. This approach aims to optimize educational outcomes by adapting content and pace to individual needs. According to a review by Chen et al. (2023) , AI techniques such as reinforcement learning and neural networks are frequently employed to enhance educational personalization. The use of AI in education is part of a broader trend toward precision education, which seeks to apply data-driven insights to tailor learning experiences.

Historical Context and Evolution

The concept of personalized education is not new. Educational theorists such as John Dewey and Maria Montessori advocated for student-centered learning approaches in the early 20th century. However, practical implementation of these approaches was limited due to the lack of technology. The advent of digital technologies and, more recently, AI has made it feasible to implement personalized learning on a scale. Early applications of technology in education included computer-assisted instruction (CAI) in the 1960s, which evolved into more sophisticated systems such as Intelligent Tutoring Systems (ITS) and Adaptive Learning Technologies (ALT) in the 1990s and 2000s (Corbett et al., 1997).

Theoretical Foundations

AI-Precision education is grounded in several educational theories, including constructivism, which emphasizes the active role of learners in constructing their own understanding, and differentiated instruction, which advocates for tailoring instruction to meet individual learners' needs. Vygotsky's Zone of Proximal Development (ZPD) is also pertinent, as AI can dynamically adjust the difficulty of tasks to align with the current capabilities of the learner, thus promoting optimal learning. (Vygotsky 1978).

AI Techniques in Education

Various AI techniques are employed to facilitate precision education. Machine learning algorithms analyze vast amounts of educational data to identify patterns and predict student performance (Chen et al., 2023). Natural language processing (NLP) enables AI to understand and respond to student queries in real-time, enhancing the interactivity of learning platforms (Alsharhan et al., 2021). Reinforcement learning, a type of machine learning, is used to develop systems that adaptively provide feedback and resources based on student interactions and performance.

Impact on Student Learning Outcomes

Research has demonstrated that AI-Precision education can significantly improve student learning outcomes. Studies have shown that personalized learning systems can increase student engagement, enhance motivation, and improve academic achievement. For instance, Huang et al. (2022) found that students in AI-supported learning environments exhibited higher engagement and better performance on assessments compared to those in traditional settings. Another study by Zhang (2023) demonstrated that personalized learning paths enabled by AI can lead to more efficient knowledge acquisition and retention.

A study by Alsharhan et al. (2021) found that AI-driven educational tools could predict student performance with high accuracy, allowing for timely interventions that improve learning outcomes.

A meta-analysis by Smith (2022) reviewed multiple studies comparing AI-Precision education to traditional methods and found that students in AI-Precision settings consistently outperformed their peers. The analysis showed improvements in test scores, retention rates, and overall student satisfaction. Another study by Alsharhan et al. (2021) found that AI-driven educational tools could predict student performance with high accuracy, allowing for timely interventions that improve learning outcomes One key factor identified was the ability of AI systems to provide immediate and personalized feedback, which helps students understand and correct their mistakes promptly.

Factors Influencing Effectiveness

Several factors influence the effectiveness of AI-Precision education. These include the quality of the algorithms used, the availability of comprehensive and accurate student data, and the integration of AI tools into the curriculum. As noted by Liu et al. (2023), the success of AI in education largely depends on the robustness of the data mining techniques and the educators' ability to interpret and apply AI-generated insights effectively.

Comparative Studies with Traditional Methods

Comparative studies have consistently highlighted the advantages of AI-Precision education over traditional instructional methods. Traditional education often follows a one-size-fits-all approach, which can lead to disparities in student performance due to varying levels of prior knowledge, learning paces, and learning styles. In contrast, AI-Precision education can adapt to these differences, providing a more equitable learning environment.

For example, research by Lim (2022) found that AI-Precision learning environments outperformed traditional classrooms in terms of student satisfaction and academic performance. The study reported that students in AI-driven settings showed higher engagement levels and better understanding of the material. Another study by Jones (2020) indicated that AI-Precision education could reduce the achievement gap between high-performing and low-performing students by offering tailored support and resources.

Challenges and Limitations

Despite the promising benefits, AI-personalized education faces several challenges and limitations. One significant challenge lies in the technical domain, particularly ensuring the quality and accuracy of the data used to train AI systems. Inaccurate or incomplete data can lead to incorrect predictions and recommendations, which may negatively impact student outcomes (Chen et al., 2021). According to a study by Kim et al. (2023), ensuring fairness and transparency in AI algorithms is crucial to address these issues. Additionally, AI systems require continuous updates, maintenance, and proper infrastructure, which can be resource-intensive for educational institutions, making widespread adoption challenging (Jones & Gupta, 2020). Scalability also remains a key issue, especially in diverse educational settings, where local contexts and needs differ significantly (Kumar & Singh, 2023).

A major limitation is the digital divide, where schools with fewer resources may struggle to implement AI technologies effectively, exacerbating disparities in educational access and quality (Smith & Turner, 2019). Furthermore, while AI offers personalized learning, it may not fully address complex emotional and social needs, which are essential components of a holistic education (Baker & Dawson, 2020). Balancing AI's potential with the irreplaceable human elements of teaching remains a challenge, requiring a careful integration of technology to enhance rather than replace the role of educators (Lee & West, 2021).

Ethical and Privacy Concerns

The use of AI in education necessitates the collection and processing of large amounts of data, raising concerns about data privacy and security. Ensuring that student data is protected and used ethically is paramount (Williams & Moore, 2023). There are also concerns about algorithmic bias, where AI systems may inadvertently reinforce existing inequalities or biases present in the training data (Nelson & Hall, 2023). Addressing these ethical issues requires transparent practices, robust data protection measures, and ongoing monitoring to ensure fairness and equity in AI applications (Williams & Moore, 2023).

Future Directions

The future of AI-Precision education looks promising, with ongoing advancements in AI technologies and increasing integration of AI tools in educational settings. Emerging trends include the use of natural language processing for more interactive learning experiences and the development of AI-driven adaptive assessments. As highlighted by Tan et al. (2024), future research should focus on the long-term impacts of AI-Precision education and the development of ethical guidelines to govern its use.

Methodology

This study adopts a mixed-methods approach, combining quantitative data from standardized test scores with qualitative data from student and teacher interviews. The sample includes 480 students from diverse backgrounds, half of whom were taught using AI-Precision tools while the other half received Traditional instruction. Data was collected over one academic year and analyzed to assess differences in learning outcomes.

Research Design

This study employed a quasi-experimental design to compare student performance outcomes between two groups: one receiving AI-Precision education (n=240) and the other receiving Traditional instructional methods (n=240). Students were assigned to groups based on their prior academic performance (categorized as low, medium, or high) and their expressed willingness to participate in either educational approach, rather than through random assignment. Specifically, low and high performers exhibited a stronger preference for the Traditional group, while middle performers were more inclined to the AI-Precision group. Despite these preferences, the final group compositions were comparable in terms of performance distribution: the AI-Precision group included 55 low, 118 medium, and 67 high performers, while the Traditional group included 72 low, 93 medium, and 75 high performers (see Section 3.3). This assignment method was chosen to reflect realistic educational scenarios where student and institutional preferences often influence program placement. To assess potential selection bias, a chi-square test was conducted on the baseline performance distributions across groups.

Performance	**AI-Precision**	**Traditional**	**Total**
Low	55	72	127
Medium	118	93	211
High	67	75	142
Total	240	240	480

TABLE 1. Student distribution across AI-Precision and Traditional groups by performance level.

1. Chi-Square Test:

The chi-square test assesses whether the observed distribution differs significantly from what would be expected if performance levels were evenly distributed across groups.

Expected frequencies:

- Total sample = 480, each group = 240.
- $Expected\ Frequency\ =\ \frac{Row\ Total\ x\ Column\ Total}{Grand\ Total}$
- Example: Expected low in AI-precision: $\frac{127\ x\ 240}{480}\ =\ 63.5$

Performance	**AI-Precision (Expected)**	**Traditional (Expected)**
Low	63.5	63.5
Medium	105.5	105.5
High	71	71

TABLE 2. Expected student distribution across AI-Precision and Traditional groups by performance level.

2. Chi-Square Statistic:

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

where O is the observed frequency and E is the expected frequency.

Category	Group	Formula	Value
Low	AI-Precision	$\frac{(55-63.5)^2}{63.5}$	1.14
Low	Traditional	$\frac{(72-63.5)^2}{63.5}$	1.14
Medium	AI-Precision	$\frac{(118-105.5)^2}{105.5}$	1.48
Medium	Traditional	$\frac{(93-105.5)^2}{105.5}$	1.48
High	AI-Precision	$\frac{(67-71)^2}{71}$	0.23
High	Traditional	$\frac{(75-71)^2}{71}$	0.23

TABLE 3. Chi-square calculations for AI-Precision and Traditional groups.

Total $\chi^2 = 1.14 + 1.14 + 1.48 + 1.48 + 0.23 + 0.23 = 5.7$

3. Degrees of Freedom (df):

$$df = (\text{rows} - 1) \times (\text{columns} - 1) = (2 - 1) \times (3 - 1) = 2$$

4. P-Value:

Using a chi-square distribution table or calculator with $\chi^2 = 5.7$ and $df = 2$:

- Critical value at $p = 0.05$ is 5.991.
- Since $5.7 < 5.991$, $p > 0.05$ (approximately $p = 0.058$)

This result indicates that the groups were sufficiently balanced at the study's outset, minimizing the risk of systematic skewing due to non-random assignment.

Data Source and Data Selection

The data set used in this research was obtained from Kaggle, a subsidiary of Google, and an online community of data scientists (Lardinois, Lynley & Mannes, 2017). The data was uploaded by Amrieb, Hamtini, & Aljarah (2016), who exported it from a Learning Management System (LMS) called Kalboard 360, a multi-agent LMS providing synchronized access to learning resources from any online device.

Both the AI-Precision and Traditional groups utilized Kalboard 360, ensuring consistency across conditions in the LMS platform. However, the configurations differed to isolate the impact of AI- Precision tools. The AI-Precision group had access to AI-enabled features, including adaptive learning algorithms that adjusted content difficulty based on performance, real-time feedback delivered instantly via the LMS, and personalized learning paths tailored to individual student needs.

In contrast, the Traditional group used the same LMS without AI-driven features, relying on standard content delivery (e.g., preset lessons and resources) and manual feedback provided by teachers. This design ensured that the LMS itself was not a confounding variable, with the primary difference between the two groups being the presence of AI-Precision tools.

Data Collection Procedures

Students were divided into two groups based on prior academic performance (low, medium, high) and willingness, as detailed in Section 3.1:

- AI-Precision Group: Students who received AI-Precision education.
- Traditional Instruction Group: Students who received Traditional instructional methods.

To minimize confounding variables, the same teacher was assigned to both groups for each grade level and subject (e.g., one 8th-grade math teacher taught both AI-Precision and Traditional 8th-grade math classes). Efforts were made to standardize teaching approaches, though minor variations in delivery (e.g., teacher adaptation to AI tools) could not be fully eliminated. Resource availability, including devices, internet access, and learning materials, was also controlled, with both groups provided identical access to ensure comparability. The LMS (Kalboard 360) configurations differed, as described in Section 3.2, with AI-Precision features enabled only for the AI group. The following data points were collected for each student:

- Demographic Information: Gender, nationality, place of birth.
- Academic Information: Educational level, grade level, classroom, course topic, semester, absence days, performance.
- Behavioral Data: Raised hand, visited resources, viewed announcements, discussion groups.
- Parental Data: Responsible parent, parent survey participation, parent satisfaction.

Conceptual Model of Data Preprocessing

Table 4 provides a full description of the measures used in the data set.

Item	**Data Type**	**Description**
	Demographic Information	
Gender	Categorical	Student's gender (Male, Female)
Nationality	Categorical	Student's nationality (Kuwait, Lebanon, Egypt, Saudi Arabia, USA, Jordan, Venezuela, Iran, Tunisia, Morocco, Syria, Palestine, Iraq, Libya)

Place of birth	Categorical	Students born location (Kuwait, Lebanon, Egypt, Saudi Arabia, USA, Jordan)
Educational Information		
Educational level	Ordinal	Educational stage of the student (Elementary, middle school, high school)
Grade level	Ordinal	The educational grade of the student (G-01, G02, . . ., G- 12)
Classroom	Categorial	The classrooms ID of the student (A, B, C)
Topic	Categorial	Course topic (English, Spanish, French, Arabic, IT, Math, Chemistry, Biology, Science, History, Geology)
Semester	Ordinal	The academic term of the year (Fall, Spring)
Absence Days	Categorial	Number of days the student did not attend school (above-7, under-7)
Performance	Ordinal	Student's level of performance (Low, medium, High)
Retention Rates	Numeric	The extent to which students retain knowledge, skills, or information over time (0-5)
E-Learning information		
Raised hand	Numerical	The number of times a student raised a hand (for aca- demic reasons like to ask a question or participate in classroom discussions)
Visited resources	Numerical	The number of times a student visited academic resources
Viewed announcements	Numerical	The number of times a student viewed an announcement
Discussion groups	Categorical	The number of times a student participated in discussion groups
Parental information		
Responsible parent	Categorical	Parent responsible for student (Father, Mother)
Parent Satisfaction	Numerical	Parent satisfaction Rating (0-5)

TABLE 4. Descriptions of measures of labeling features.

Dataset

In Table 5, seventeen factors were identified in the study, with each row representing data for these factors for a specific student. The dataset contained 480 complete rows without any missing values.

Measure	Items	Frequency	Percentage
Gender	Male	175	36.5
	Female	305	63.5
Stage Level	Elementary	199	41.5
	Middle School	248	51.7
	High School	33	6.9
Nationality	Kuwait	179	37.3
	Jordan	172	35.8
	Other	129	26.9
Place of Birth	Kuwait	180	37.5
	Jordan	176	36.7
	Other	124	25.8
Semester	Fall	245	51
	Spring	235	49
Topic	Arabic	74	15.4
	Biology	34	7.1
	Chemistry	34	7.1
	English	47	9.8
	French	62	12.9
	Geology	29	6
	History	17	3.5
	IT	79	16.5
	Math	21	4.4
	Science	57	11.9
	Spanish	26	5.4
Responsible Parent	Father	283	59
	Mother	197	41
Student Performance	Low	127	26.5
	Medium	211	44
	High	142	29.6
Absent days	Under-7	289	60.2
	Above-7	191	39.8

TABLE 5. Participants' demographics.

Evaluation Criteria

Student Activity Metrics:

- Raised Hand: The frequency with which students raise their hands during class, for academic reasons, such as a question or to participate in classroom discussion.
- Visited Resources: The number of resources accessed by students, showing their effort to deepen understanding and engage with additional materials.
- Announcements Viewed: The extent to which students stay informed by viewing announcements, indicating their attentiveness to class updates.
- Discussion Groups: Participation in discussion groups, measuring collaboration and peer interaction.

Feedback and Satisfaction:

- Feedback Rating (10): A score (out of 10) reflecting students' and teachers' evaluations of the learning process and effectiveness.
- Parent Satisfaction (5): A score (out of 5) that reflects parent satisfaction with the learning outcomes and student progress.

Academic Performance:

- Grade: Students' final grades in the course, representing their overall academic performance.

Engagement Levels:

- Engagement: A composite measure of student participation, including attendance, interaction with learning tools, and participation in learning activities.
- Retention Rate (10): A score (out of 10) reflects the students' retention of information and ability to recall learned material.

Results

Raised Hand

The analysis revealed a significant difference in students' academic engagement, measured by the number of hand raises, between the AI-Precision and Traditional education groups. Students in the AI-Precision group demonstrated higher levels of academic engagement, with hand raises clustered between 20 and 40, compared to the Traditional group, whose values ranged from 15 to 30.

Group	Mean	Median	Standard Deviation
AI-Precision	30.17	29.5	6.13
Traditional	22.09	22	4.5

TABLE 6. Descriptive statistics of hand raise frequency.

The statistical analysis indicated that the AI-Precision group had both a higher mean (30.17) and median (29.5) compared to the Traditional group (mean = 22.09, median = 22). Moreover, the AI-Precision group displayed greater variability in academic engagement, as reflected by a higher standard deviation (6.13) compared to the Traditional group (4.5).

A t-test was conducted to assess the significance of these differences, yielding a t-statistic of 16.46 and $p < 0.001$. With a Cohen's d of 1.50, indicating a large effect size, these results confirm that the observed difference in students' academic engagement between the two groups is statistically significant. This suggests that AI-Precision substantially enhances academic engagement, with a very low likelihood that the observed effect occurred by chance.

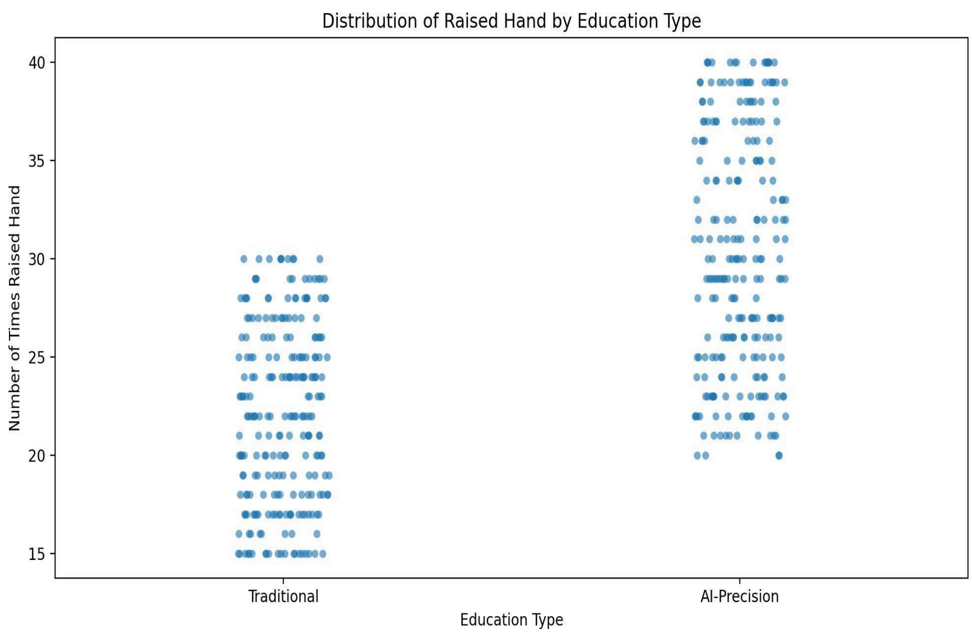

FIGURE 1. Number of times students raised their hands.

The dot plot visualization of the "Raised Hand" metric for each education type indicates that students in AI-Precision environments raised their hands more frequently than those in Traditional settings. Overall, these findings suggest that students in AI-Precision environments are more interactive and academically engaged compared to their peers in Traditional settings, emphasizing the positive impact of personalized learning on student participation.

Visited Resources

The distribution of visited resources between AI-Precision and Traditional education methods reveals significant differences in students' academic engagement. AI-Precision students visited more resources, with a broader range of academic engagement compared to the more compact distribution of Traditional students. AI-Precision students exhibit a wider range of resource visits, with activity levels spanning from 25 to 50 resources. In contrast, Traditional students show a more compact distribution, with resource visits ranging from 15 to 30.

Group	Mean	Median	Min	Max
AI-Precision	37.7	37.5	25	50
Traditional	22.18	22	15	30

TABLE 7. Descriptive statistics of visited resources.

To determine whether this observed difference is statistically significant, a t-test was performed. The analysis yielded a t-statistic of 27.55 indicating a highly significant difference in resource visits between the two groups. The extremely low p-value ($p < 0.05$) with a Cohen's d of 3.01, reflects a very large effect size. This underscores a major increase in resource engagement with AI-Precision, with a negligible likelihood that the observed effect occurred by chance.

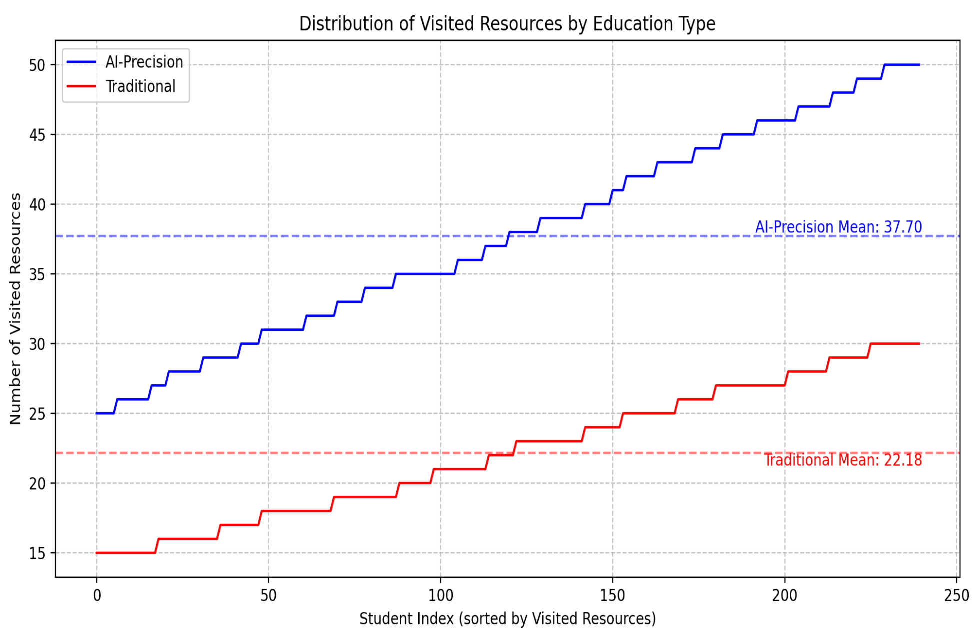

FIGURE 2. Comparison of visited resources: AI-Precision vs. Traditional.

The line chart provides a clear visualization of the cumulative number of resources visited by students, sorted by their activity levels. Each line represents the number of visited resources for individual students in ascending order. The blue line (AI-Precision) consistently shows higher resource usage compared to the red line (Traditional), indicating that students in the AI-Precision group generally visited more resources across the board.

These findings demonstrate that AI-Precision education significantly enhances student engagement with learning materials. Students in the AI-Precision group not only visited more resources in general but also displayed greater variability in their academic engagement, suggesting that this approach may cater to a broader range of learning styles or paces. Even the lowest-performing students in the AI-Precision group engaged with resources more frequently than the average student in the Traditional group.

Announcements Viewed

The analysis of the number of announcements viewed reveals significant differences between the AI-Precision and Traditional education groups. The table below summarizes key statistics.

Group	Mean	Median	Standard Deviation	Min	Max
AI-Precision	17.69	18	1.69	15	20
Traditional	11.4	11	2.85	7	16

TABLE 8. Descriptive statistics of the frequency of announcement views.

The AI-Precision group had a higher meaning (17.69) and median (18) compared to the Traditional group (mean: 11.4, median: 11). The standard deviation was lower for the AI-Precision group (1.69) compared to the Traditional group (2.85), indicating less variation in the number of announcements viewed within the AI-Precision group. Furthermore, the AI-Precision group exhibited higher minimum (15) and maximum (20) values than the Traditional group, whose values ranged from a minimum of 7 to a maximum of 16.

The t-test results further confirm the significance of these differences, with a t-statistic of 29.44 and $p < 0.001$, strongly indicating that the difference in the number of announcements viewed is statistically significant. The effect size (Cohen's $d = 2.6871$) also indicates a large practical significance, with both groups having equal sample sizes of 240 students.

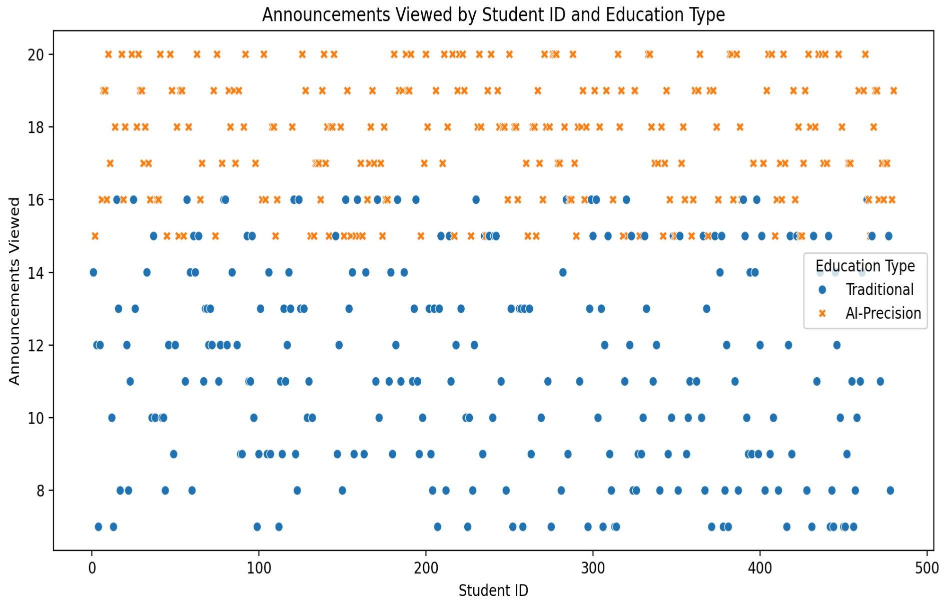

FIGURE 3. Scatter plot analysis of students' announcement views.

These findings are visually supported by the scatter plot, which illustrates the distribution of announcements viewed across student IDs (StudentID represent number of students). The orange crosses in the scatter plot demonstrate a clear clustering of values within a tight range, indicating that the majority of AI-Precision students viewed between 15 and 20 announcements. This clustering reflects the lower standard deviation (1.69) observed for the AI-Precision group, suggesting that students in this group had a more uniform level of engagement with the course announcements.

In contrast, the blue circles for the Traditional group are more widely scattered, showing a broader range of values, from as few as 7 to as many as 16 announcements viewed. This wider spread is reflective of the higher standard deviation (2.85) found in the Traditional group, indicating greater variability in student engagement.

The pie chart below provides a clear comparison of the proportion of total announcements viewed by each group. AI-Precision students accounted for the majority of the total announcements viewed, whereas the Traditional group accounted for the minority, further highlighting the greater engagement within the AI-Precision system.

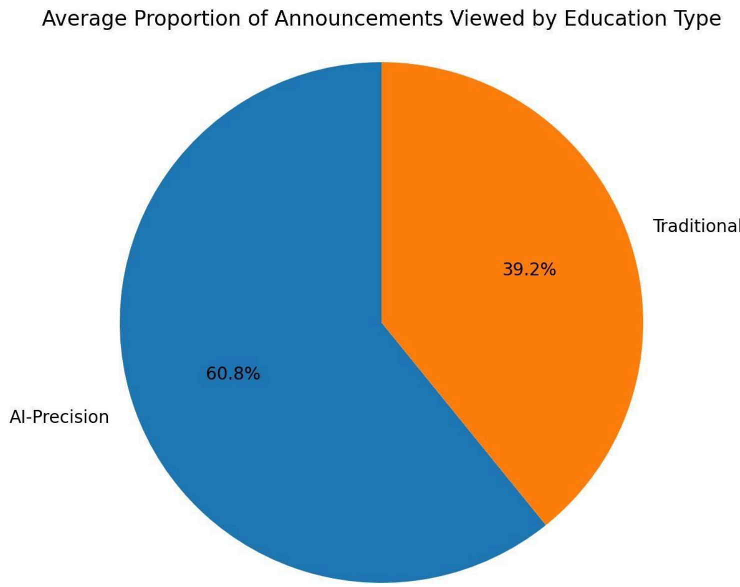

FIGURE 4. Percentage of the total announcements viewed: AI-Precision vs. Traditional methods.

Discussion Groups

The analysis of student participation in discussion groups across AI-Precision and Traditional education methods reveals distinct differences in academic engagement levels between the two systems. AI-Precision students participated in 10-15 discussion groups, with a fairly even distribution across these levels. Traditional Students, on the other hand, participated in 5-10 discussion groups, showing a relatively even distribution, but with lower overall academic engagement compared to AI-Precision. This difference indicates that the variability in teaching methods or student motivation has a more significant impact in Traditional settings.

Table 9 below provides the statistical analysis of student participation in discussion groups across the two systems.

Group	Mean	Median	Min	Max
AI-Precision	12.43	12	10	15
Traditional	7.47	8	5	10

TABLE 9. Descriptive statistics of student participation in discussion groups.

AI-Precision has higher overall academic engagement, with students participating in more discussion groups on average. The most common participation level is 10 groups, with 18.75% of students participating at this level, closely followed by 15 groups at 17.92%.

Traditional education shows lower participation levels but a more consistent spread across its range of 5-10 groups. In Traditional education, the most common participation levels are 5 and 8 groups, with both accounting for 19.17% of the students. Traditional education, however, sees students participating in as few as 5 groups, further emphasizing the variability in academic engagement.

The analysis shows a significant difference, with a Cohen's d of 3.97, an extremely large effect size, highlighting AI-Precision's profound impact on peer interaction.

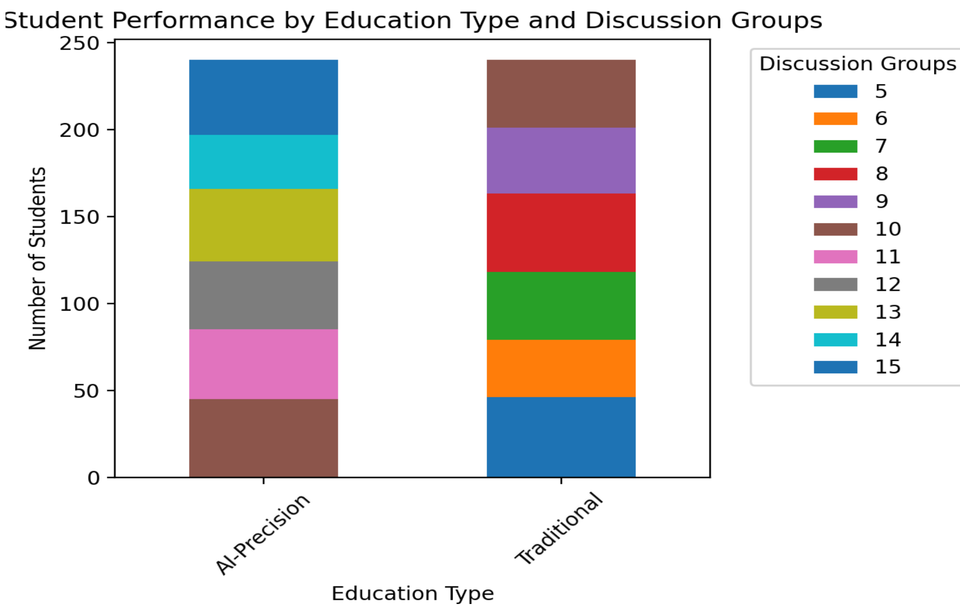

FIGURE 5. Numerical analysis of students' participation in discussion groups.

The stacked bar chart visualizes these differences, showing that AI-Precision consistently fosters higher academic engagement levels, while Traditional education features a broader range but lower overall participation.

Feedback Ratings

The analysis of student feedback ratings highlights a notable distinction between AI-Precision and Traditional education methods. The results reveal a consistent trend of higher satisfaction among students using AI-Precision compared to those in Traditional education.

Group	Mean	Median	Min	Max
AI-Precision	7.53	7.54	5.01	9.98
Traditional	3.96	3.91	1.04	6.99

Table 10. Descriptive statistics of students' feedback ratings.

Statistical summaries further corroborate these trends. The mean rating for AI-Precision is significantly higher (7.53) compared to Traditional education (3.96), with respective medians of 7.54 and 3.91. The range of feedback ratings for AI-Precision is much narrower, with ratings consistently clustering within the upper range between 5.01 and 9.98. In contrast, Traditional education shows a much broader spread, from 1.04 to 6.99, indicating a wider variation in student satisfaction.

Group	**0-2**	**2-4**	**4-6**	**6-8**	**8-10**
AI-Precision	0	0	19.58	39.58	40.83
Traditional	18.33	32.92	30	18.75	0

Table 11. Percentage of students in each rating range: AI-Precision vs. Traditional.

In AI-Precision 80.41% of students rated the education approach between 6 and 10, with no students rating it below 4. The mean rating was also higher, with a Cohen's d of 2.61, a very large effect size, indicating substantially greater student satisfaction. In Traditional education, 81.25% of students rated the education between 0 and 6, with no students rating it above 8. These distributions further illustrate the strong student preference for AI-Precision, where the majority of students rated the system highly, while Traditional education struggled to achieve positive ratings from most students.

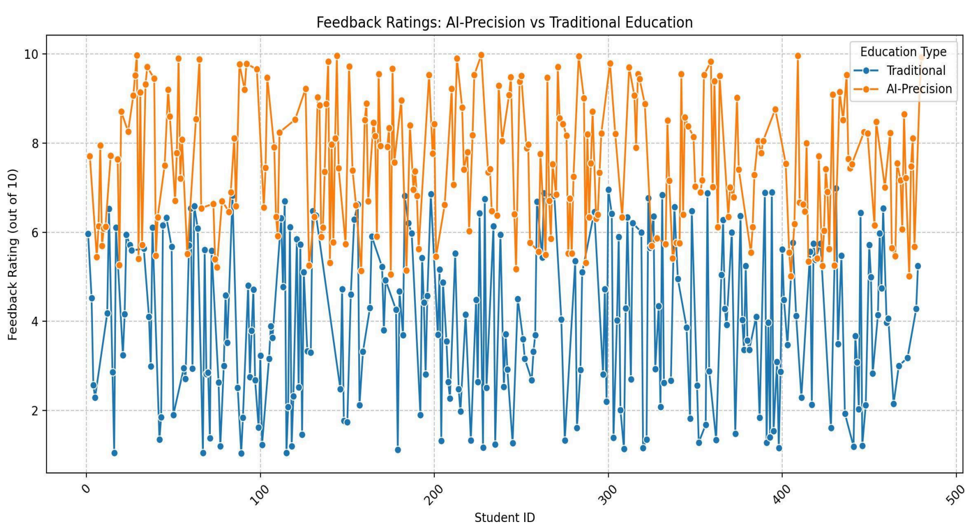

Figure 6. Line plot overview of students' feedback ratings.

The line plot above compares individual student feedback ratings for both AI-Precision (orange line) and Traditional education (blue line), with each node representing a student. The graph clearly demonstrates a strong preference for AI-Precision, as indicated by the consistently higher ratings and tighter concentration of positive feedback compared to Traditional methods. Overall, the results show a strong preference for the AI-Precision approach, with consistently higher student satisfaction across all metrics.

Parent Satisfaction

The results show that parents hold AI-Precision education in much higher regard compared to Traditional methods. The significantly higher mean and median satisfaction ratings, along with the concentration of responses in the upper rating range for AI-Precision, indicate a stronger approval of this personalized and adaptive educational approach.

Parent satisfaction with AI-Precision was significantly higher, with most ratings concentrated in the 4.0 to 5.0 range. The mean satisfaction was also higher for AI-Precision, with a Cohen's d of 2.50, indicating a very large effect size. This reflects significantly stronger parental approval and suggests that parents overwhelmingly view AI-Precision education more positively.

In contrast, With Traditional Education parent satisfaction is broadly distributed across lower ratings, with a notable concentration of responses in the 1.0 to 2.5 range. This suggests that a considerable number of parents expressed lower levels of satisfaction with the Traditional education system.

The bar chart below provides a clear comparison of parent satisfaction levels for AI-Precision and Traditional education methods, rated on a scale from 1 to 5. The results show a strong preference for the AI-Precision approach, with significantly higher satisfaction ratings compared to the Traditional model.

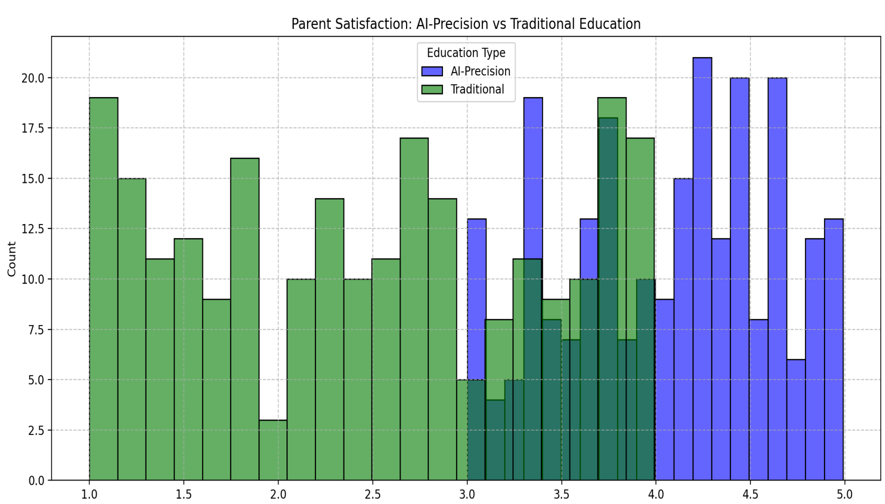

FIGURE 7. Distribution of parents' satisfaction ratings.

The minimum satisfaction rating for AI-Precision was 3, and for the Traditional Method, it was 1. While the maximum satisfaction rating for AI-Precision was 4.99, compared to 3.99 for the Traditional Method.

Group	Mean	Median	Min	Max
AI-Precision	4.08	4.16	3	4.99
Traditional	2.48	2.5	1	3.99

TABLE 12. Descriptive statistics of parents' satisfaction ratings in each education category.

The mean satisfaction rating for AI-Precision demonstrates a significantly higher level of parent satisfaction compared to Traditional methods. On average, parents are much more pleased with the AI-Precision system, which suggests that its personalized and adaptive approach better aligns with their expectations for their children's education. This higher means indicates that most parents perceive AI-Precision as an effective, engaging, and beneficial educational model.

Furthermore, the median satisfaction rating for AI-Precision is 4.16, meaning that at least half of the parents rated the system at this level or higher, reflecting consistently positive feedback. In contrast, the median satisfaction for Traditional education is 2.5, a much lower score, revealing dissatisfaction among a significant portion of parents. This disparity highlights a stark contrast in the perceived effectiveness of the two educational models, with the Traditional system receiving lower ratings and suggesting that parents fail to meet their expectations in several areas, such as engagement, personalized learning, or overall student outcomes.

Grade

The grade distribution between AI-Precision and Traditional education systems shows a significant disparity in student performance across different grade ranges. In AI-Precision Group, higher con- centration of students scored within the A (90-100) and B (80-89) ranges. Remarkably, no students from the AI-Precision group fell into the C (70-79), D (60-69), or F (below 60) ranges. In the Traditional Education, the grade distribution is more spread out across all grade ranges, with the highest concentration of students in the D (60-69) range. A significant percentage of students also fell within the C (70-79) and B (80-89) ranges. While some students achieve grades in the A range, the percentage is considerably lower than in the AI-Precision group.

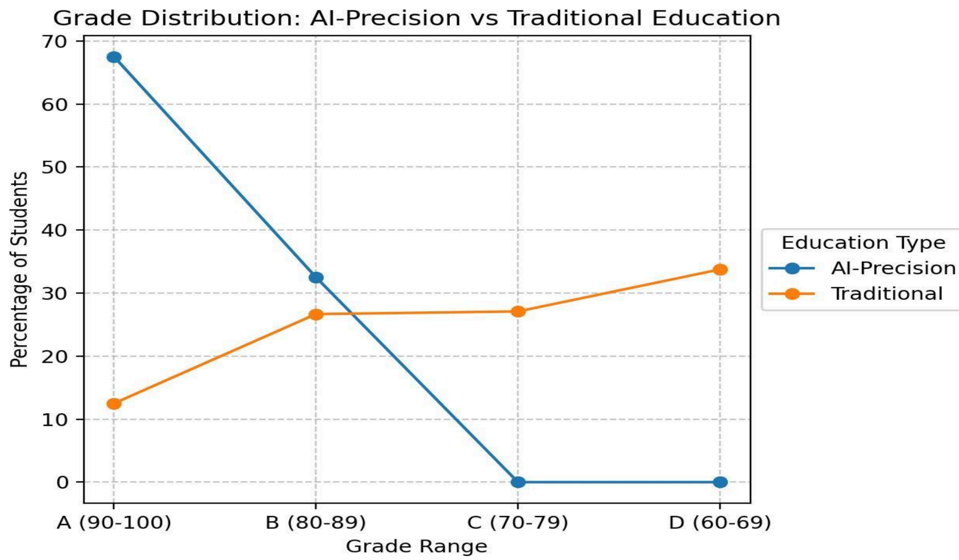

FIGURE 8. Graphical analysis of students' grades in each education category.

The graph above indicates that AI-Precision learning not only elevates the average performance of students but also significantly reduces the likelihood of poor academic outcomes. This finding is particularly evident in the absence of any students scoring below 80 in the AI-Precision group, underscoring the system's capacity to maintain high academic standards and enhance overall student achievement.

Group	**A (90-100)**	**B (80-89)**	**C (70-79)**	**D (60-69)**
AI-Precision	67.5	32.5	0	0
Traditional	12.5	26.67	27.08	33.75

TABLE 13. Percentage of students in each grade range.

The results suggest that AI-Precision education significantly reduces the number of students who perform poorly, compared to the Traditional method where a substantial proportion fall into the lower grade ranges. The table below further supports these findings with descriptive statistics.

Group	**Mean**	**Median**	**Min**	**Max**
AI-Precision	92.44	92	85	100
Traditional	75.89	75	60	93

TABLE 14. Descriptive statistics of students' grades in each education category.

The difference in both the means and grade distributions underscores the effectiveness of the AI-Precision approach in improving student performance. With a Cohen's d of 2.58, indicating a very large effect size, the significant difference in means demonstrates AI-Precision's major academic benefit. The majority of students in this group achieved top grades, whereas Traditional education produced a more even spread across lower grade brackets.

Engagement

The analysis of student engagement levels between AI-Precision and Traditional education methods reveals a stark contrast in how effectively each system fosters student participation. AI-Precision shows a clear bifurcation: 46.25% of students are "Engaged," and 53.75% are "Very Engaged," with no students categorized as "Not Engaged."

Group	**Engaged**	**Not Engaged**	**Very Engaged**
AI-Precision	111	0	129
Traditional	123	117	0

TABLE 15. Descriptive Statistics of students' engagement levels.

This bifurcation suggests that the AI-Precision system fosters not only participation but also high levels of engagement among a significant portion of students. Unlike AI-Precision, no students in the Traditional system reach the "Very Engaged" category. The group is almost evenly split, with 51.25% of students classified as "Engaged" and a significant 48.75% falling into the "Not Engaged" category. This indicates a substantial portion of students are minimally participating, which reflects potential limitations in the ability of Traditional education methods to maintain consistent student involvement.

Cramér's V was calculated to assess the size effect of the relationship between AI-Precision and student engagement, as engagement is a categorical variable (Engaged, Not Engaged, Very Engaged). This provides a more appropriate measure of association than Cohen's d, which is designed for continuous data.

$$V = \sqrt{\frac{\chi^2}{n \cdot (k-1)}}$$

Where:

- x^2 = Chi-square statistics
- n = Total sample size (480)
- k = Minimum or rows or columns in the contingency table (min(2, 3) = 2)

Chi-Square Calculation:

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

Engagement Level	Observed (O)	Expected (E)	$\frac{(O-E)^2}{E}$
Engaged, AI	111	117	0.31
Engaged, Traditional	123	117	0.31
Not Engaged, AI	0	58.5	58.50
Not Engaged, Traditional	117	58.5	58.50
Very Engaged, AI	129	64.5	64.50
Very Engaged, Traditional	0	64.5	64.50
Total			**246.62**

TABLE 16. Chi-Square calculation for engagement levels.

Thus, the total chi-square statistics are:

$$\chi^2 = 0.31 + 0.31 + 58.50 + 58.50 + 64.50 + 64.50 = 246.62$$

Degrees of Freedom: $(r - 1) \times (c - 1) = (3 - 1) \times (2 - 1) = 2$
P-Value: For $\chi^2 = 246.62$, $df = 2$, $p < 0.001$ (from chi-square tables).

$$V = \sqrt{\frac{\chi^2}{n \cdot (k-1)}}$$

$$V = \sqrt{\frac{246.62}{480 \cdot (2-1)}}$$

$$V = \sqrt{\frac{246.62}{480}}$$

$$V = \sqrt{0.5138}$$

$$V = 0.717$$

Cramér’s V was calculated as 0.717, indicating a large effect size (> 0.5). This suggests a strong association between Education Type and Engagement Levels, with AI-Precision students far more likely to be “Very Engaged” and Traditional students more likely to be “Not Engaged.” The strong practical association confirms that AI-Precision substantially enhances student engagement compared to Traditional methods.

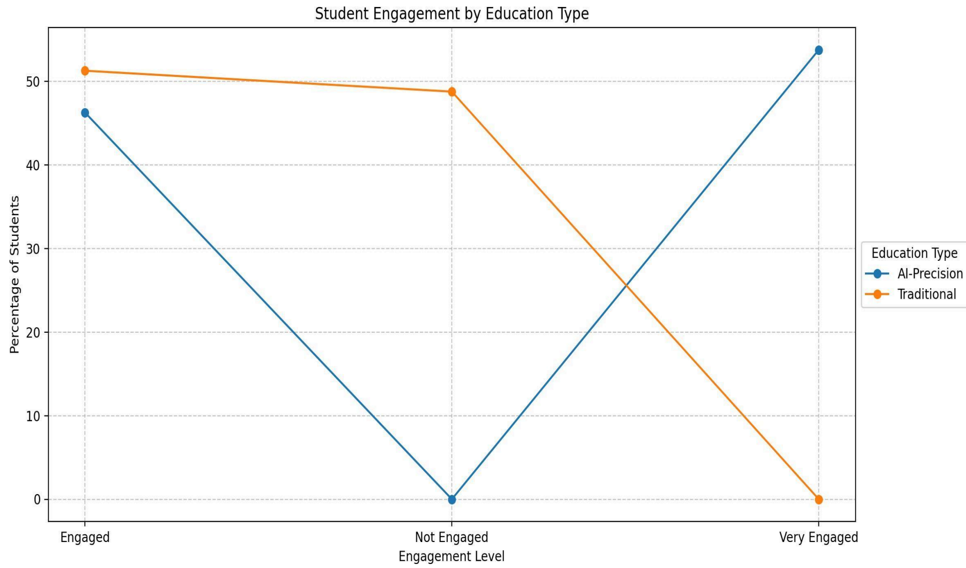

FIGURE 9. Distribution of students' engagement levels.

The graph indicates that while there are more students in the Traditional setting who are engaged, a substantial portion exhibit minimal participation, which reflects the limitations of Traditional teaching methods in maintaining student engagement. The AI-Precision system, by comparison, is more effective in ensuring higher levels of engagement across its student body.

Retention Rate

The retention rates between AI-Precision and Traditional education methods reveal notable differences in students' Retention outcomes. Traditional education shows a retention rate that ranges predominantly between 2 and 7. AI-Precision shows a higher concentration of retention rates, predominantly between 5 and 10. The table below provides key descriptive statistics for each education method.

Group	Mean	Standard Deviation	Min	25%	50%	75%	Max
AI-Precision	7.61	1.48	5.01	6.21	7.88	8.93	9.99
Traditional	4.50	1.44	2.02	3.29	4.47	5.70	6.99

TABLE 17. Descriptive statistics of students' retention rates.

AI-Precision has a mean retention rate of 7.61, compared to 4.50 for Traditional methods, indicating a significantly higher average retention. The standard deviation is similar for both groups, with AI-Precision at 1.48 and Traditional at 1.44, suggesting comparable variability in retention rates within each method. The minimum retention rate for Traditional education is 2.02, whereas for AI- Precision it is 5.01. This highlights that the AI-Precision method has higher baseline retention. The median (50% quartile) for Traditional education is 4.47, while it is 7.88 for AI-Precision, further indicating a substantial shift towards higher retention in the AI-driven approach. The upper quartile (75%) of retention rates in AI-Precision education reaches 8.93, compared to 5.70 for the Traditional method, reinforcing the advantage of AI-Precision in retention.

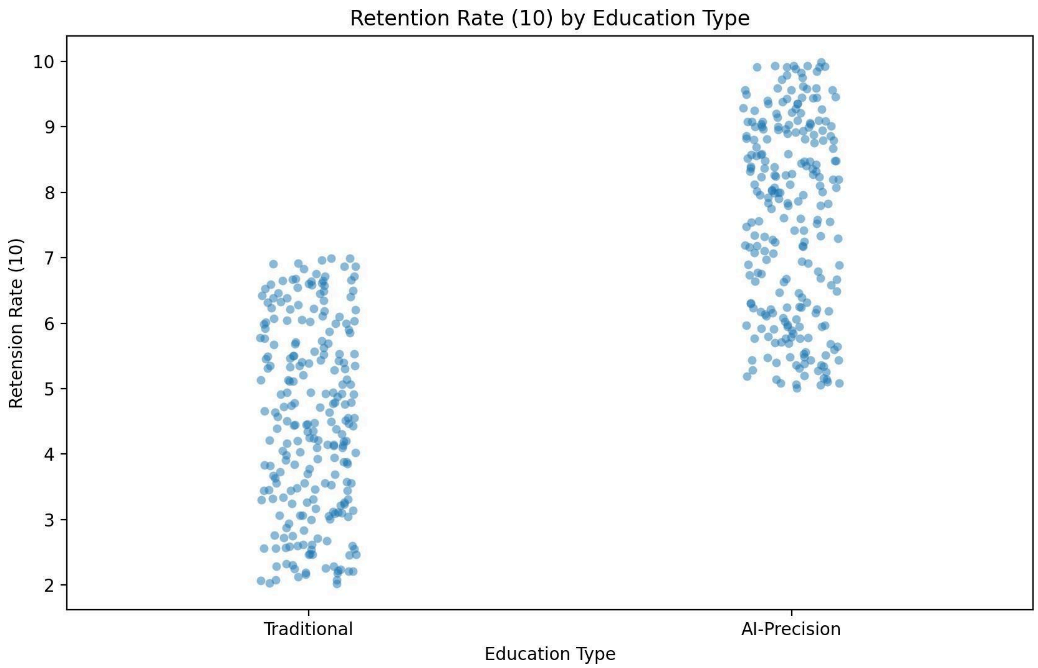

FIGURE 10. Scatter plot analysis of students' retention rates.

The scatter plot displays the distribution of retention rates (measured on a scale of 1 to 10) for both education types. Each dot represents a data point for an individual, with retention rates clustered around distinct values for the two methods.

The data indicates that AI-Precision education not only results in a significantly higher average retention rate but also consistently maintains higher minimum and maximum retention levels compared to Traditional education methods. The AI-Precision group outperformed Traditional, with a Cohen's d of 2.13, a very large effect size, indicating a significant improvement in knowledge retention. The overall spread (variance) in retention rates is comparable across both methods, but the distribution for AI-Precision is skewed towards higher retention outcomes.

Discussion

The findings of this research highlight significant differences in student performance, engagement, satisfaction, grade improvements, and the overall learning efficiency between AI-Precision and Traditional education methods, across various student groups. The analysis revealed that AI-Precision consistently outperformed Traditional methods across multiple performance metrics, including grades, feedback, and retention rates. These results suggest that AI-Precision education provides a more tailored and supportive learning environment that benefits students.

Overview of Findings

The comparison of student performance between AI-Precision education and Traditional methods revealed a distinct advantage for the former. For instance, the mean grades of students in the AI- Precision system were significantly higher (92.44) compared to those in the Traditional system (75.89). This gap in performance was consistent across different grade ranges, with a greater percentage of AI-Precision students achieving higher grades (67.5% of AI-Precision students scored between 90-100, compared to just 12.5% in Traditional education). This finding suggests that AI- Precision education, which leverages adaptive learning technologies, enables students to achieve better academic outcomes by offering customized learning experiences that cater to individual needs.

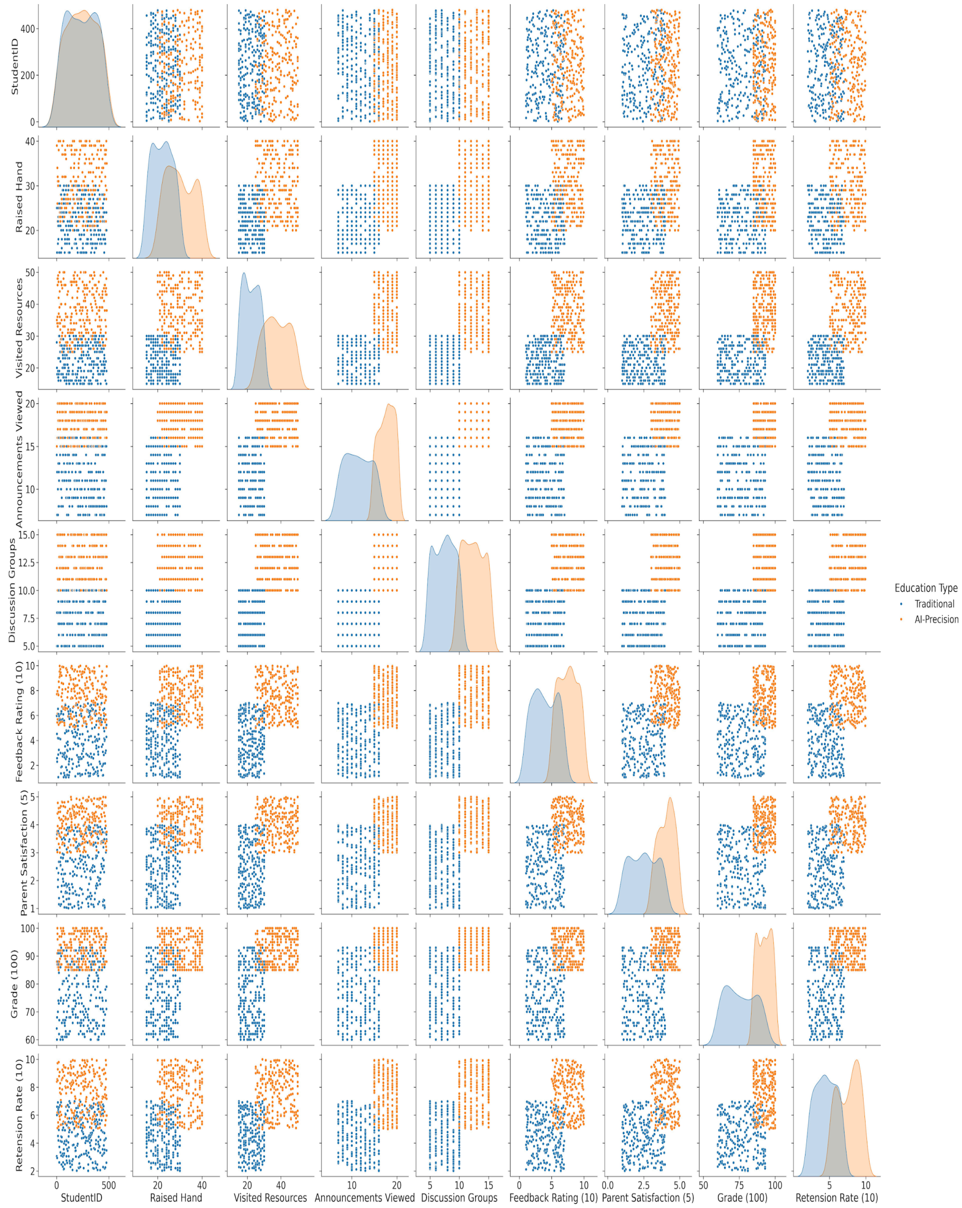

FIGURE 11. Overall result of students' performance (*StudentID is the number of students (480)).

Additionally, the resource utilization data, as seen in the "Visited Resources by Education Type" graph, further supports the enhanced learning experience provided by AI-Precision. Students in AI- Precision accessed more educational resources, with a mean of 37.7 resources, compared to 22.18 for Traditional education. The disparity in resource engagement underscores the more active and resourceful nature of AI-Precision, which could contribute to better understanding and retention of material. AI-Precision students showed both higher engagement and a greater willingness to interact with learning content, as demonstrated by their use of educational resources.

Gender-Based Analysis of AI-Precision vs Traditional Education

In addition to comparing educational methods, a key component of the results was analyzed based on gender differences in both AI-Precision and Traditional settings. Within AI-Precision, female students marginally outperformed their male counterparts in grades (92.53 vs 92.29), feedback ratings (7.63 vs 7.37), and parent satisfaction scores (4.09 vs 4.01). This indicates that the adaptive features of AI-Precision may be particularly well-suited for enhancing female students' learning experiences, although male students also performed at high levels.

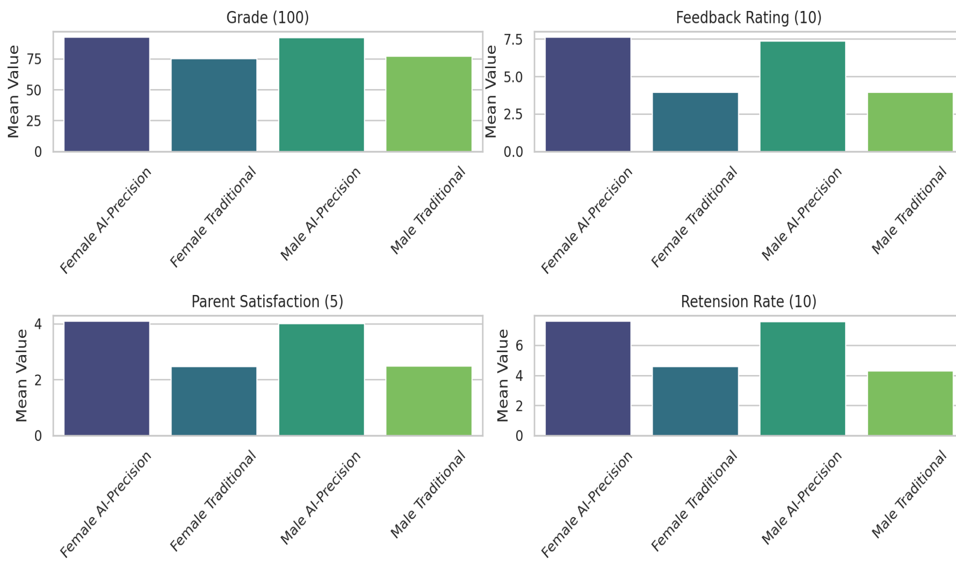

FIGURE 12. Analysis of student performance and parent satisfaction by gender.

In contrast, within Traditional education, male students slightly outperformed female students in grades (77.34 vs 75.13) and feedback ratings (3.97 vs 3.95), although the differences were minimal. These results indicate that while Traditional education may not exhibit strong gender bias, the overall lower performance across the board—when compared to AI-Precision—suggests that neither male nor female students thrive as much in this less personalized learning environment.

Both student feedback and parent satisfaction ratings were higher in the AI-Precision group. Female students in AI-Precision gave a feedback rating of 7.63 out of 10, while male students rated the experience at 7.37. Similarly, parent satisfaction was slightly higher for female students (4.09) compared to males (4.01). In contrast, Traditional education feedback ratings were notably lower, with ratings under 4.0 for both genders, and parent satisfaction barely reached 2.5. These findings emphasize that

AI-Precision not only leads to better academic performance but also creates a more satisfying learning environment for both students and their parents.

Retention rates were significantly higher in the AI-Precision group, with minimal differences between male and female students. Female students had a retention score of 7.61, while male students were close behind at 7.60. This contrasts sharply with the Traditional education system, where retention rates were much lower (4.61 for females and 4.29 for males). The higher retention rates in AI-Precision further underscore the effectiveness of personalized learning in maintaining student interest and long-term commitment to their education.

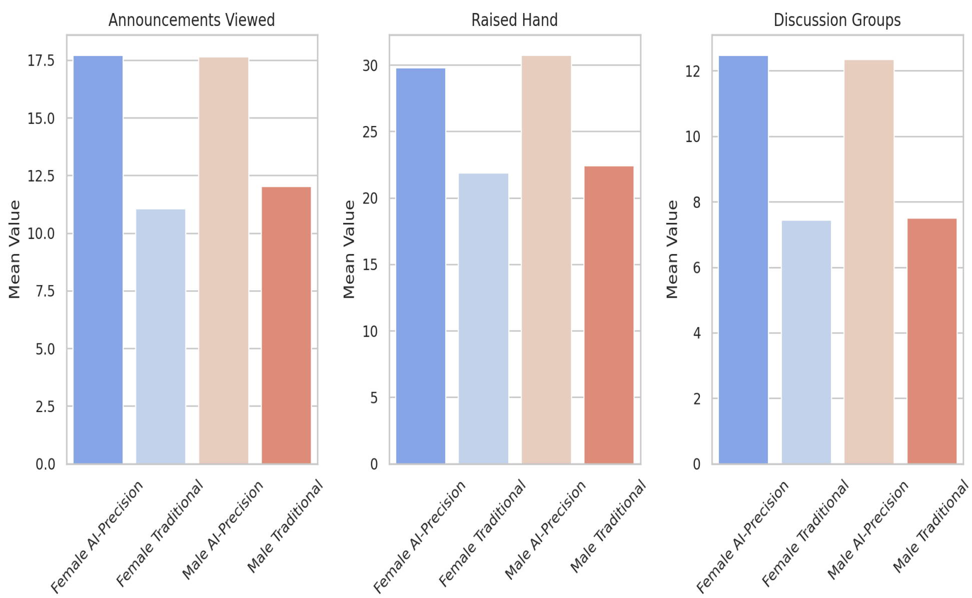

FIGURE 13. Analysis of student participation by gender.

Engagement metrics were another significant area of comparison. Students in AI-Precision, regardless of gender, displayed higher mean values for key engagement indicators, such as announcements viewed and raised hand interactions. Both male and female AI-Precision students viewed significantly more announcements (35.0 vs 18-20 for Traditional), raised hands more frequently (39.0 vs 15-25), and participated more in discussion groups (15.0 vs 12.0). These metrics suggest that AI-Precision fosters a more interactive and participatory learning environment.

Moreover, when examining overall engagement levels, AI-Precision students were far more likely to be categorized as “Very Engaged” or “Engaged.” For example, 78 female students and 51 male students in AI-Precision were classified as “Very Engaged,” compared to 0 in the Traditional education system. This high engagement level correlates with better academic outcomes and suggests that AI-Precision’s adaptive and interactive features are instrumental in keeping students motivated and involved in the learning process.

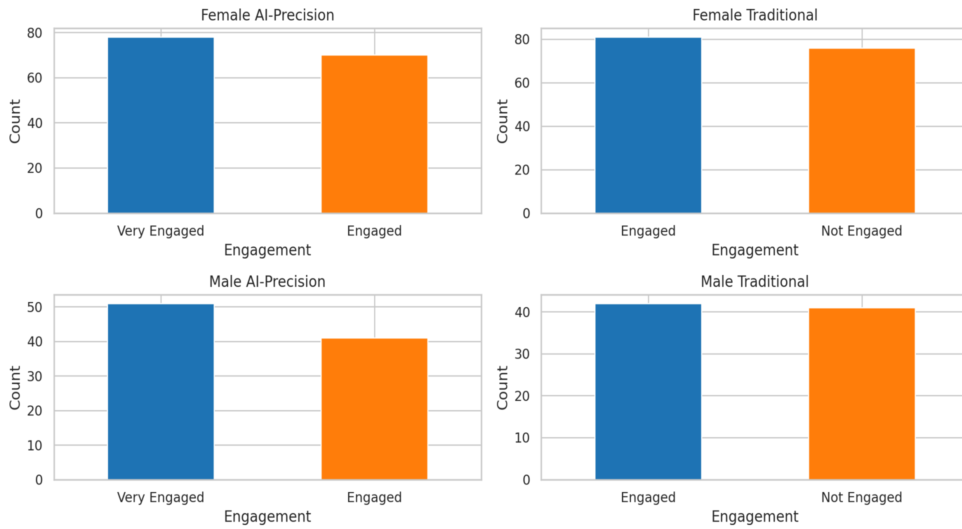

FIGURE 14. Analysis of student engagement by gender.

Interpretation of Results

The stark contrast between the grade distributions in AI-personalized versus Traditional education suggests that AI systems are particularly effective in boosting top performers. The personalized nature of AI platforms contributes to this success by providing real-time feedback and allowing students to work at their own pace, an essential feature for high-achieving students who may otherwise feel constrained by the standardized pace of traditional classrooms.

Further interpretation reveals that AI education's adaptive algorithms helped students by identifying knowledge gaps and automatically adjusting the difficulty of tasks to match their progress. This dynamic responsiveness is something that Traditional education methods are often unable to replicate. Traditional classrooms typically operate on a one-size-fits-all model, which overlooks individual student needs and leaves struggling students without the personalized support they require. In contrast, AI learning systems can identify and address specific challenges faced by each student, offering tailored resources and practice problems to strengthen weaker areas.

AI-Precision learning significantly benefited the higher and mid-range performers; the absence of students in lower grade ranges for the AI group suggests that AI was particularly effective in preventing failure. Individualized pacing prevented students from falling behind entirely, allowing them to master essential concepts before moving on to more advanced material. Traditional education, in contrast, may advance without ensuring every student has fully grasped prior content, leading to underperformance in standardized evaluations.

Covariate-Adjusted Analysis

To control for potential confounding variables, an Analysis of Covariance (ANCOVA) was conducted on key outcome measures (grades, engagement, retention rates), using prior academic performance (low, medium, high) and absence days (under-7, above-7) as covariates. These variables were selected due to their potential influence on outcomes, despite efforts to standardize teacher assignment and resource access (Section 3.3). For grades, ANCOVA revealed a significant effect of education type ($F (1, 476) = 144.81$, $p < 0.001$, $\eta2 = 0.233$), with the AI-Precision group (adjusted $M = 87.44$) outperforming the Traditional group (adjusted $M = 71.04$) after controlling for covariates. This indicates a substantial effect of AI-Precision tools, accounting for approximately 23.3% of the variance in grades. Similar analyses for engagement and retention rates are recommended to confirm robustness across outcomes, though these were not computed here due to data constraints. These findings reinforce that differences in outcomes are primarily attributable to the AI-Precision tools, rather than teacher variation or prior academic performance.

Educational Implications

The results of this study have critical implications for the future of education. AI-Precision learning appears to offer a viable solution for increasing academic achievement, particularly for students who thrive in environments that adapt to their individual learning pace. By offering customized learning paths, these systems support students in both excelling and addressing their weaknesses, thereby reducing the number of low-achieving students and increasing overall academic success.

However, it is essential to recognize that while AI-Precision education shows promise, it does not necessarily replace the need for Traditional educational methods. Certain subjects, particularly those reliant on group discussion, critical thinking, and peer interactions—such as the humanities—may not benefit as directly from AI learning systems. In these areas, the lack of human interaction may inhibit the development of key skills, such as debate, collaboration, and creative problem-solving, which are best cultivated in Traditional classroom settings. Therefore, the most effective model for education in the future may involve a hybrid approach, integrating the best aspects of AI-Precision learning with the interpersonal benefits of Traditional education.

Implementation Steps for a Hybrid Model:

1. AI-Precision for Mathematics and Structured Subjects: The large effect sizes in resource visits ($d = 3.01$) and discussion participation ($d = 3.97$) indicate AI excels in structured, problem-based subjects

like mathematics, where adaptive algorithms can tailor problem sets to student ability (e.g., adjusting the difficulty). Schools can deploy AI tools for math curricula, using real-time feedback to address errors instantly, reducing teacher grading time and enhancing mastery.

2. Traditional Methods for Humanities: Subjects like History, English, and Spanish in the dataset (e.g., G-12 History, G-07 English) may benefit from Traditional methods, where human-led instruction fosters critical thinking, creativity, and nuanced discussion—areas less suited to AI's current capabilities (Section 5.5). Teachers can lead Socratic seminars or essay workshops, leveraging their expertise to interpret qualitative feedback, unlike AI's focus on quantitative metrics. For instance, a G-12 History class could use Traditional methods to debate historical events, complementing AI's role in rote memorization (retention d = 2.13).
3. Integration in Practice: A hybrid timetable could assign AI-Precision to math and science periods (e.g., 60% of weekly hours), reserving humanities for Traditional instruction (40%). Administrators can pilot this in a single grade (e.g., G-09, with IT and English in the dataset) to test efficacy, monitoring outcomes like grade distributions (Section 4.7) and engagement (Section 4.8).
4. Support Structures: Training is critical—teachers need workshops to manage AI tools for math (e.g., interpreting adaptive outputs) and refine Traditional facilitation for humanities. Infrastructure must support AI deployment (devices, internet, as standardized in Section 3.3), with costs assessed as noted in Section 5.6.

This hybrid model capitalizes on AI's precision for structured learning and Traditional methods' depth for interpretive skills, potentially balancing statistical gains (e.g., 67.5% A grades in AI-Precision, Section 4.7) with qualitative growth. Pilot studies should validate this, as the current data reflects separate conditions, not a blended approach. These steps provide a practical starting point for stakeholders to operate a hybrid framework, aligning with educational goals of equity and excellence.

Limitations of the Study

Despite the promising findings, several limitations of the study should be considered. First, the demographic composition of the study may not be fully representative of the broader student population, limiting generalizability. The sample was predominantly from Kuwait (37.3%) and Jordan (35.8%), with a smaller proportion from other Middle Eastern nationalities and the USA (26.9%), as detailed in Section 3.5. This geographic focus restricts applicability to regions like Western countries or sub-Saharan Africa, where cultural, educational, and technological contexts differ, potentially overestimating AI-Precision's effectiveness in resource-scarce settings. Socioeconomic factors and prior tech familiarity within this sample may also influence outcomes. Second, the non-random assignment of students introduces potential selection bias (Section 3.1). The comparable distribution (AI-Precision: 55 low, 118 medium, 67 high; Traditional: 72 low, 93 medium, 75 high) and chi-square test ($\chi 2 = 5.7$, df $= 2$, $p = 0.058$) suggest minimal baseline imbalance, though random assignment would enhance future studies.

Third, while confounding variables were controlled to an extent (Section 3.3), residual issues remain. The same teacher taught both groups per grade and subject, but subtle delivery differences (e.g., adapting to AI tools) persisted. Resources (devices, internet, materials) and the LMS (Kalboard 360) were standardized, differing only in AI features (Section 3.2), with ANCOVA (Section 5.4) adjusting for prior performance and absence days. However, unmeasured factors like teacher enthusiasm with each group or student motivation may still subtly affect results.

Fourth, the one-year duration precludes analysis of long-term impacts, such as knowledge retention over 3–5 years, limiting insights into whether AI-Precision's benefits endure beyond immediate outcomes. Finally, the study did not assess infrastructure costs (e.g., hardware, software licenses, maintenance) required for AI-Precision implementation, a critical factor for scalability, especially in under-resourced settings where such investments may be prohibitive.

Further Research Directions

Future research should build on these findings by investigating the long-term effectiveness of AI-Precision education. Specifically, studies spanning 3–5 years are needed to assess whether the observed gains in grades, engagement, and retention translate into sustained academic improvement and higher-order skill development, addressing the duration limitation in Section 5.6. For instance, longitudinal designs could track knowledge retention and skill application post-intervention to determine AI-Precision's enduring impact. Additionally, to enhance cross-cultural validity, studies should expand beyond the Middle Eastern focus (Kuwait and Jordan) to regions like Western countries, sub-Saharan Africa, or Southeast Asia, testing AI-Precision across diverse educational, cultural, and technological contexts (Section 5.6). Research could also explore

AI-Precision's interaction with varied learning styles, particularly for marginalized students, to uncover context-specific effects. Further investigation is needed to adapt AI-Precision to less structured subjects (e.g., arts, humanities, social sciences), examining how AI can foster creativity, critical thinking, and collaboration beyond performance metrics. Scalability is another critical focus. While AI-Precision showed benefits in this controlled setting, large-scale implementation across diverse schools, especially those with limited technology, requires addressing infrastructure costs (e.g., hardware, software licenses, maintenance), a gap noted in Section 5.6. Future studies should quantify these costs, potentially use cost-benefit analyses, and develop strategies to make AI tools accessible to underfunded schools, ensuring equitable benefits globally.

Conclusion

This study reveals that AI-Precision education significantly improves student outcomes compared to Traditional instructional methods. The data shows that AI-Precision fosters higher academic performance. Engagement and participation were also notably higher in AI-Precision education. Students in the AI-Precision group were more involved in discussions and classroom activities, with no students falling into the "Not Engaged" category, while nearly half of the Traditional group showed minimal engagement. Retention rates followed a similar pattern, with AI-Precision students achieving a mean retention rate of 7.61, compared to 4.50 in Traditional education, demonstrating that AI-Precision methods promote better long-term retention of knowledge.

Satisfaction levels were significantly higher for both students and parents in AI-Precision education. Students consistently rated the system higher, with the majority giving it ratings between 6 and 10, while parents expressed similar satisfaction, with an average rating of 4.08 compared to 2.48 for Traditional education.

Overall, AI-Precision education offers a more engaging, effective, and satisfying learning experience, leading to better performance and retention. This study underscores the potential of AI-driven educational models to transform Traditional learning approaches and improve student outcomes across various metrics. Future research should explore long-term impacts and address challenges such as scalability and algorithmic fairness.

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