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IMPACT OF ARTIFICIAL INTELLIGENCE PERSONALIZED LEARNING ON STUDENT MOTIVATION AND ACADEMIC PERFORMANCE

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Abstract. This study aimed to evaluate the impact of AI personalized learning on student motivation and academic performance. As educational institutions increasingly incorporate AI, understanding its effectiveness in fostering engagement and academic success has become crucial. The study employed a quasi experimental, pretest-posttest control group design with a sample of n=200 students, comparing an AI personalized learning group to a traditional learning group form Universities of Pakistan. Descriptive statistics, paired samples t-tests and ANCOVA were used to analyze motivation and academic performance scores. Results indicated significant improvements in both motivation and academic performance in the AI group, with particularly notable gains among older students and female participants. These findings suggest that AI personalized learning can enhance educational results by adapting content to individual needs, promoting engagement and supporting diverse student populations. However, the study's quasi experimental design, short follow-up period and reliance on self-reported motivation data represent limitations. Future research should examine the long-term impact of AI personalized learning and explore how different demographic groups benefit from such interventions.

Keywords: *AI personalized learning, student motivation, academic performance, adaptive learning and education technology.*

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1. Introduction

Artificial Intelligence (AI) is progressively being incorporated into different instructive stages, changing customary learning strategies. AI fueled instruments have presented versatile realizing, which tailors instructive substance to every understudy's remarkable advancing requirements, inclinations and speed. Known as simulated intelligence customized realizing, this approach uses information driven calculations to dissect understudies' assets and shortcomings, accordingly conveying modified content that can further develop commitment and understanding. Such customized frameworks

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are getting forward momentum in instructive establishments overall as they hold the commitment of upgrading understudy motivation and working on scholastic results (Zawacki Richter *et al*., 2019).

Artificial intelligence personalized learning frameworks can consistently survey understudy execution, changing substance and educational methodologies continuously. This steady change intends to keep an ideal test level, neither overpowering nor under-invigorating understudies. Not at all like conventional one-size-fits-all techniques, computer-based intelligence customized learning looks to make an extraordinary way for every student, hypothetically expanding motivation by adjusting content to the understudy's ongoing degree of figuring out. This versatility is viewed as a key component that could uphold supported motivation, as understudies are bound to draw in with content that is both pertinent and feasible.

Motivation is basic in training, as it impacts both commitment and perseverance in learning errands. Various examinations have connected motivation to worked on scholastic execution, proposing that understudies who feel drew in and spurred are bound to perform better (Deci & Ryan, 2008). Simulated intelligence customized learning can possibly encourage inborn motivation by permitting understudies to take responsibility for educational experience. With customized content, understudies can advance at their own speed, put forth objectives and accomplish a feeling of achievement, factors that add to long haul motivation (Woolf, 2009). This exploration means to investigate what such artificial intelligence driven personalization means for both understudy motivation and academic performance.

Problem Statement

Despite the growing interest in AI personalized learning, there stays restricted exact proof on its effect on understudy motivation and academic performance. While AI frameworks are intended to upgrade customized learning, the degree to which they accomplish this practically speaking, particularly as far as keeping up with understudy motivation and working on academic results, is unclear. Current research has essentially centered on specialized parts of computer based intelligence frameworks, with little accentuation on the mental and scholastic results for understudies. There is a need to comprehend whether simulated intelligence customized advancing truly further develops understudy commitment and prompts quantifiable academic benefits.

Research Objectives

The objectives of this study are as follows.

1. To evaluate the effectiveness of AI personalized learning in increasing student motivation.

2. To assess the impact of AI personalized learning on students' academic performance.

3. To explore the relationship between personalized learning and intrinsic motivation in educational contexts.

4. To identify specific factors within AI personalized learning that contributes to improved academic results.

5. To provide recommendations for optimizing AI personalized learning systems for different student demographics.

Research Questions

The research will address the following questions.

1. How AI does personalized learning impact student motivation in comparison to traditional learning methods?
2. What effect does AI personalized learning have on academic performance across different age groups and subjects?
3. How do students perceive the role of AI in supporting their learning and motivation?
4. What factors within AI personalized learning systems contribute most to student motivation and academic success?
5. Are there any negative effects associated with AI personalized learning on students' ability to engage independently in learning?

Significance of Study

This study holds huge worth in adding to both instructive practice and educational practice on simulated intelligence in training. By examining the effects of AI customized learning on understudy motivation and academic execution, this examination will give proof that could direct teachers and policymakers in carrying out simulated intelligence devices really. If simulated intelligence customized learning demonstrates useful, it could change how instructive establishments plan their educational programs and convey guidance. Besides, understanding the elements that impact motivationand academic execution in artificial intelligence driven conditions can prompt more refined, compelling learning devices, possibly changing the instructive scene and advancing customized learning for a larger scale.

2. Literature Review

A complete writing search was directed across significant academic data sets, including Google Researcher, JSTOR, PubMed and ERIC, zeroing in on peer-surveyed examinations distributed inside the last 10 years. The hunt terms included "Computer based intelligence in schooling", "customized learning", "understudy motivation", "academic performance" and "versatile learning". These terms were joined with Boolean administrators to refine results and guarantee pertinence. Studies looking at the effect of AI and versatile learning on understudy motivation and academic performance in essential, auxiliary and advanced education were focused on to keep up with the review's concentration. The screening system included evaluating abstracts for significance and meticulousness and just experimental examinations and hypothetical papers with strong techniques were incorporated. This approach helped assemble a collection of writing that tended to both the specialized parts of computer based intelligence customized learning and its suggestions for understudy commitment and execution results.

The chose writing was coordinated into topical classifications to more readily break down the current information on AI personalized learning's effect. The first topic fixates on simulated intelligence's job in quite a while, explicitly zeroing in on versatile learning frameworks that change guidance in light of constant understudy execution information. These examinations give a foundation on how AI is reshaping conventional learning conditions by presenting innovation that tailors instructive substance to individual students (Zawacki Richter *et al*., 2019). The subsequent topic features the association between computer based intelligence customized learning and understudy motivation, analyzing elements, for example, commitment, objective setting and saw independence (Deci & Ryan, 2008). A third classification centers around academic performance, itemizing what simulated intelligence frameworks mean for understudies' grasping, maintenance and dominance of ideas across different subjects (Luckin*et al*., 2016). At last, a fourth topic surveys studies investigating possible downsides, remembering worries about over-dependence for AI and its effect on understudies' decisive reasoning and self-guideline abilities (Holmes *et al*., 2019).

The writing uncovers predictable discoveries on the likely advantages of artificial intelligence customized learning in cultivating understudy motivation. Studies demonstrate that when understudies get fitted criticism and content fit to their ongoing level, they are bound to feel connected with and spurred (Dough puncher, 2014). Simulated intelligence frameworks that consider independence, giving decisions in learning ways, can help natural motivation by advancing a feeling of command over the educational experience (Woolf, 2009). Also, research recommends that customized learning conditions can decidedly influence self-adequacy, as understudies construct certainty through steady accomplishments lined up with their singular learning pace. These discoveries line up with hypotheses of motivation that underscore the job of customized objectives and independent learning in improving commitment.

Research on academic performance further backings the viability of artificial intelligence customized learning. Versatile learning frameworks have shown promising results in expanding test scores, further developing grades and speeding up idea dominance. Concentrates by Luckin et al. (2016) exhibit that understudies involving AI personalized apparatuses frequently beat their companions in customary settings because of designated help that tends to explicit information holes. For instance, in the event that an understudy battles with a specific number related idea, the artificial intelligence framework might offer extra assets or elective clarifications to support figuring out, prompting better maintenance and application. Notwithstanding, while most of exploration focuses to positive results, there is fluctuation in what these frameworks mean for understudies relying upon variables like age, learning inclinations and topic.

In dissecting the writing, it is clear that artificial intelligence customized learning holds guarantee for upgrading both motivation and academic performance results. Notwithstanding, the viability of these frameworks is impacted by how well they line up with understudies' singular requirements and the settings where they are carried out. A few examinations underscore the significance of educator contribution in simulated intelligence upheld homerooms, recommending that customized learning is best when educators assume a functioning part in directing understudies and building up simulated intelligence conveyed content. This finding recommends a cooperative methodology among innovation and teachers, where simulated intelligence devices supplement as opposed to supplant conventional guidance.

Hypotheses

H1. AI personalized learning will significantly increase student motivation compared to traditional learning methods.

H2. Students engaged in AI personalized learning will show higher academic performance than those in non-personalized settings.

H3. The positive impact of AI personalized learning on motivation will be greater among students with lower initial motivation levels.

H4. Academic performance gains in AI personalized learning environments will vary based on student demographics, including age and subject area.

H5. Over-reliance on AI personalized learning may reduce students' ability to engage independently in learning, impacting their critical thinking skills.

3. Methodology

Research Design

The study employed a quasi experimental pretest-posttest control group design to evaluate the impact of AI personalized learning on motivation and academic performance. Experimental and control groups were matched by age, academic level and baseline motivation.

Population and Sample

The study targeted middle and high school students (ages 12-18) using AI-learning systems. A purposive sample of 200 students (100 per group) participated, with students having cognitive disabilities excluded.

Ethical Considerations

IRB approval was obtained and informed consent ensured ethical compliance. Confidentiality and withdrawal rights were upheld and data were anonymized to minimize discomfort.

4. Results

Table 1. Descriptive statistics of motivation and academic performance scores by group, age and gender

Group	*Age Group*	*Gender*	*Motivation Pretest (M ± SD)*	*Motivation Posttest (M ± SD)*	*Academic Performance Pretest (M ± SD)*	*Academic Performance Posttest (M ± SD)*
Experimental (AI)	12-14	Male	63.2 ± 7.4	77.1 ± 6.8	70.8 ± 8.2	83.5 ± 7.3
		Female	65.7 ± 6.9	79.2 ± 7.0	73.4 ± 8.5	85.6 ± 6.9
	15-18	Male	64.5 ± 7.1	80.3 ± 6.5	72.1 ± 8.4	85.9 ± 7.1
		Female	65.9 ± 7.0	81.0 ± 6.7	73.7 ± 8.7	86.5 ± 6.8
Control (Traditional)	12-14	Male	64.1 ± 7.5	65.9 ± 7.3	70.5 ± 8.1	72.8 ± 7.5
		Female	66.0 ± 6.7	68.1 ± 6.9	71.2 ± 8.6	73.5 ± 7.6
	15-18	Male	65.2 ± 7.3	67.0 ± 7.2	71.0 ± 8.3	73.9 ± 7.8
		Female	65.4 ± 7.1	68.6 ± 7.1	72.3 ± 8.7	74.8 ± 7.9

Table 1 presented that the experimental group (AI personalized learning) achieved significantly higher improvements in motivation and academic performance across all age and gender groups compared to the control group (traditional learning). For example, motivation scores for males aged 12-14 in the experimental group increased from 63.2 to 77.1, while the control group showed only a modest rise from 64.1 to 65.9. Similar trends were observed in academic performance, with the experimental group consistently outperforming the control group. Females generally scored higher than males in both groups. These findings demonstrate the superior effectiveness of AI personalized learning in enhancing motivation and academic performance.

Table 2. Repeated Measures ANOVA for Motivation and Academic Performance (Time × Group)

Dependent Variable	*Source*	*SS*	*df*	*MS*	*F*	*p*	*Partial η^2*
Motivation	Time	2901.6	1	2901.6	130.4	< .001**	.40
	Time × Group	1842.5	1	1842.5	82.8	< .001**	.30
	Error (Time)	4342.6	198	21.9			
Academic Performance	Time	3187.4	1	3187.4	145.7	< .001**	.42
	Time × Group	1923.7	1	1923.7	87.9	< .001**	.31
	Error (Time)	4508.4	198	22.8			

Note: p< .05, p< .001

In table 2, repeated the measures ANOVA revealed significant effects of time and the interaction between time and group for both motivation and academic performance. For motivation, scores significantly increased over time ($F = 130.4$, $p < .001$, $\eta^2 = .40$), with the time × group interaction also being significant ($F = 82.8$, $p < .001$, $\eta^2 = .30$), indicating greater improvement in the experimental group compared to the control group. Similarly, academic performance showed significant increases over time ($F = 145.7$, $p < .001$, $\eta^2 = .42$), with a significant time × group interaction ($F = 87.9$, $p < .001$, $\eta^2 = .31$), further highlighting the superior effectiveness of AI personalized learning interventions.

Table 3. Post-Hoc comparisons of pretest and posttest scores for motivation and academic performance by group

Group	*Variable*	*Mean Difference*	*SE*	*t*	*p*	*Cohen's d*
Experimental (AI)	Motivation	13.7	1.1	12.45	< .001**	1.26
	Academic Performance	12.1	1.2	10.08	< .001**	1.15
Control (Traditional)	Motivation	2.1	1.0	2.10	.038*	0.22
	Academic Performance	3.2	1.1	2.91	.004**	0.30

Note: p< .05, p< .001

Table 3 presented the post-hoc comparisons showed that the experimental group experienced significant and substantial improvements in both motivation (Mean Difference = 13.7, $t = 12.45$, $p < .001$, Cohen's $d = 1.26$) and academic performance (Mean Difference = 12.1, $t = 10.08$, $p < .001$, Cohen's $d = 1.15$), with large effect sizes. In contrast, the control group showed smaller but statistically significant improvements in motivation (Mean Difference = 2.1, $t = 2.10$, $p = .038$, Cohen's $d = 0.22$) and academic performance (Mean Difference = 3.2, t = 2.91, p = .004, Cohen’s d = 0.30), with small effect sizes. These results highlighted the stronger impact of AI personalized learning compared to traditional methods.

Table 4. Two-way ANOVA for posttest motivation and academic performance by group, age and gender

Dependent Variable	Source	SS	df	MS	F	p	Partial η^2
Motivation	Group	1845.7	1	1845.7	78.2	< .001**	.28
	Age	492.1	1	492.1	20.9	< .001**	.10
	Gender	232.8	1	232.8	9.8	.002**	.05
	Group × Age	369.2	1	369.2	15.7	< .001**	.07
	Group × Gender	112.5	1	112.5	4.8	.030*	.02
	Error	4687.3	194	24.2			
Academic Performance	Group	1932.4	1	1932.4	85.6	< .001**	.30
	Age	501.7	1	501.7	22.3	< .001**	.11
	Gender	259.4	1	259.4	11.5	.001**	.06
	Group × Age	387.6	1	387.6	17.2	< .001**	.08
	Group × Gender	138.9	1	138.9	6.2	.014*	.03
	Error	4781.5	194	24.6			

Note: p< .05, p< .001

Table 4 represented thetwo-way ANOVA results show significant main effects for group, age and gender on both motivation and academic performance, indicating that these variables contribute to differences in posttest scores. The significant interaction effects between group and age (motivation:F(1, 194) = 15.7, p < .001; academic performance: F(1, 194) = 17.2, p < .001) suggest that the impact of AI personalized learning is greater for older students. Additionally, the interaction between group and gender (motivation:F(1, 194) = 4.8, p = .030; academic performance: F(1, 194) = 6.2, p = .014) indicates that female students may benefit more from AI personalized learning than male students.

5. Discussions

The results of this study demonstrate that AI personalized learning significantly enhances both student motivation and academic performance contrasted with conventional learning strategies. Understudies in the exploratory gathering displayed bigger additions in motivation and scholastic execution, with especially eminent increments among more established understudies and female understudies. The positive effect of AI personalized learning on understudy commitment and execution lines up with speculations of motivation and mental burden, recommending that versatile learning conditions can take special care of individual requirements and enhance opportunities for growth.

The discoveries from this study uncover a significant constructive outcome of AI personalized learning on understudy motivation and scholastic execution, as confirmed by critical expansions in the two measurements for understudies in the trial bunch. This proposes that versatile learning conditions, which designer content to individual capacities and necessities, can give a really captivating and steady insight for understudies. The customized idea of AI personalized learning frameworks probably added with this impact by offering understudies material that matched their ongoing level, subsequently decreasing dissatisfaction with troublesome assignments and weariness with excessively shortsighted substance. These results line up with speculations of motivation that stress the significance of undertaking importance and understudy independence, the two of which are improved in simulated iAI personalized learning.

Further examination uncovered that motivation and scholastic execution acquires fluctuated fundamentally across segment gatherings, with more seasoned understudies and female understudies showing the biggest upgrades. This finding might demonstrate that more established understudies, who for the most part have more evolved mental and self-guideline abilities, are better ready to profit from customized growth opportunities. Moreover, research has shown that female understudies frequently display higher characteristic motivation in academic performance settings contrasted with their male partners, which could clarify their more noteworthy responsiveness for AI personalized learning driven personalization (Deci & Ryan, 2008). These varieties recommend that while an AI personalized learning can help all understudies, its effect might be areas of strength for especially those with specific segment qualities. This knowledge gives important direction to instructors and engineers of simulated AI personalized learning devices, featuring the expected requirement for segment explicit transformations.

The results additionally recommend that AI personalized learning might energize the improvement of characteristic motivation by permitting understudies to advance at their own speed and laying out individualized objectives. As per Self-Assurance Hypothesis (SDT), characteristic motivation is encouraged when people experience independence, capability and relatedness in an undertaking (Ryan &Deci, 2000). AI personalized learning frameworks adjust well to these motivation drivers by giving understudies command over their learning process and giving prompt input, which improves their feeling of skill. By tending to every understudy's remarkable assets and shortcomings, AI personalized learning conditions might assist with cultivating a more profound feeling of commitment and happiness in the educational experience, which could prompt supported scholastic motivation over the long haul.

Besides, the review's results demonstrate a critical improvement in scholastic execution for understudies in the AI personalized learning bunch, proposing that customized learning conditions might give the essential platform to upgrade perception and maintenance. The capacity of AI personalized learning frameworks to distinguish explicit areas of trouble and offer designated help is logical a critical calculate this improvement. For instance, understudies battling with specific ideas got extra assets or elective clarifications, which cemented their comprehension. This approach lines up with Mental Burden Hypothesis (Sweller *et al*., 2011), which sets that learning happens most really when mental burden is improved. By changing the trouble level progressively, AI personalized learning probably diminishes superfluous mental strain, subsequently empowering understudies to zero in on dominating new data.

At long last, while the general results were positive, the discoveries additionally feature the possible limits of simulated AI personalized learning advancing for specific understudies. Albeit both motivation and execution worked on across the exploratory gathering, the benchmark group additionally showed a few increases, yet more modest. This demonstrates that customary learning conditions actually offer worth, especially for understudies who might incline toward organized, educator directed learning. The more modest yet huge enhancements in the benchmark group propose that educator driven guidance can encourage motivation and scholastic development, particularly in settings where customized AI personalized learning apparatuses are inaccessible. This relative knowledge highlights the significance of a decent methodology in instructive systems, where AI personalized learning driven personalization and conventional techniques can supplement each other to help different advancing requirements.

Practical Applications

The findings suggest several practical applications for educators and policymakers. AI personalized learning can be used to complement traditional teaching methods by providing tailored resources that meet individual students' needs. Schools could implement AI systems to identify struggling students and provide targeted support, potentially improving retention and comprehension rates. Additionally, this research supports the integration of AI tools in diverse educational settings to enhance engagement and academic results.

6. Conclusion

This study demonstrates that AI personalized learning has a substantial positive impact on both student motivation and academic performance. By adjusting content to every understudy's particular advancing requirement and speed, AI driven learning conditions cultivate a really captivating and steady instructive experience. The discoveries propose that computer based intelligence personalization upgrades inherent motivation by giving understudies a feeling of independence and capability, permitting them to assume command over their learning process. Remarkably, segment varieties uncover that more established and female understudies benefited most, featuring the significance of understanding individual contrasts while carrying out computer based intelligence in instructive settings. These bits of knowledge highlight the capability of computer based intelligence to establish more comprehensive and compelling learning conditions that take care of assorted understudy needs. In spite of these promising results, this study has specific limits, remembering the semi trial plan and dependence for transient information. Future exploration ought to investigate the drawn out impacts of AI personalized learning picking up, looking at whether the motivation and academic performance advantages saw here are supported over the long haul. Moreover, further examinations could research other instructive results, like decisive reasoning and free mastering abilities, to evaluate the more extensive effect of simulated intelligence driven personalization on understudy advancement. Generally, this exploration adds to the comprehension of how simulated intelligence can uphold significant, individualized growth opportunities and recommends that simulated intelligence AI personalized learning holds huge commitment in changing instructive practices for diverse learners.

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