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Artificial intelligence for enhancing learning and motivation among education faculty students

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Abstract

The rapid development of Artificial Intelligent (AI) has triggered change of thoughts about conventional pedagogical patterns in educational institutions especially in relation to student involvement and educational motivation. Even though there has been significant investment in educational technology infrastructure, the modern-day education faculty programs are still grappling with a deteriorating student motivation, poor personal learning activities and a lack of readiness to work in a technology-based teaching capacity. The research filling the critical gap that is presented in this study is the empirical effectiveness of AI-based intervention targeted at education faculty students in particular, as they are in a unique position to impact the future of the educational practices. Results were obtained through a mixed-methods research design that studied undergraduate and graduate education students and three semesters using an integrated AI learning ecosystem based on adaptive learning platforms, intelligent tutoring systems, feedback mechanisms based on natural language processing, and elements of gamification. The study used structural equation modeling, hierarchical linear regression, and thematic analysis as part of the evaluation of cognitive, affective, and behavioral aspects of learning engagement. Findings showed statistically significant differences with many outcome measures of biochemical results, such as a gain in intrinsic motivation scores of 34.7, a gain in learning persistence measures of 41.2, and an increase in academic performance indicators of 28.9. In addition, qualitative results also showed paradigm changes in self-efficacy perceptions and attitude to the use of technology amongst students.

Keywords: Artificial intelligence, Education, Students, Motivation, Adaptive learning, Personalized learning.

1. Introduction

The modern educational environment is going through a fundamental change fueled by the fast development of technology, changing social needs, and developing instructions paradigm [1]. Artificial intelligence is one of such disruptive influences that have proven to be promising agents of redefining the teaching and learning services [1-2]. Although there has been a considerable part of research dedicated to the application of AI to science, technology, engineering, and mathematics fields, there has been significantly smaller empirical research on the role of AI in faculty programs in academic education, with future educators becoming ready to work in a more complex classroom setting [3-5]. The education faculty students have special challenges that set them off against what other students are in other fields of study [6-8]. These threats would encompass acquiring the dual knowledge in the field content and instructional strategies, balancing the views of complicated levels of theories and yet acquire the hands-on experience in the classroom at the same time, and be ready to meet the diverse student groups of different learning capacities and technological abilities [9]. The old-fashioned methods of teaching, which are mostly theory-driven and lecture-based, do not provide enough means to properly involve in the contemporary education students that are both digital natives and future

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practitioners of education that will have to implement the technological aspect into the teaching practice in some meaningful way.

Motivation among students is a very important dimension that determines academic performance, career growth as well as teaching performance [7,9-10]. Studies have continually shown that when students are motivated they become more persistent to difficult tasks, they are much engaged in the learning material and are able to think in more complicated metacognitive ways [1,11-14]. But the education faculty programs have a history that has not been able to sustain high motivation levels among the students despite the various long degree programs which may take a long time and have a wide course work, practicum and licensure examinations. This drop in motivation is a serious issue not only to the performance of individual students but also to the institution at large, since an uninspired student of education can later turn out to be a deteriorated teacher in a position that cannot inspire his or her students.

The technologies of artificial intelligence and the ability to customize the learning process, provide real-time feedback, adjust the content according to the requirements, and optimize the instructional process with data suggest the opportunities never experienced to tackle these motivational and engagement issues [13,15-17]. Machine learning algorithms have an ability to study the learning patterns of each individual and propose the personalized learning patterns, detect the knowledge gaps and suggest them [18-20]. The capabilities of natural language processing provide advanced automated feedback of one of written assignments and discussion postings. The intelligent tutoring systems are able to offer on-demand services to difficult conceptual knowledge [19,21-22]. The aspects of gamification that involve AI interaction can turn a simple learning session into an exciting, task-based and goal-oriented one that creates intrinsic motivation [11,23-25]. Although such theoretical benefits are present, empirical data concerning the real capabilities of AI to improve student learning and motivation in education faculty students is very scarce [26-28]. The raw materials based on existing literature usually dwell on restricted use of AI, analysed short-term results, or on student groups within various academic fields [29-32]. Additionally, a lot of research that exists is of a low methodological rigor that self-reported measures of satisfaction and not objective learning outcomes or the use of quasi-experimental designs without sufficient control of confounding factors.

Starting with this investigation, two theoretical frameworks complementary to each other have been used to offer conceptual basis to motivation in the educational context. Self-Determination Theory, which was designed by Deci and Ryan, states that human motivation would be present in a range between amotivation all the way up to extrinsic motivation up to intrinsic motivation, psychological need satisfaction serves as the mechanism that produced the quality of motivation, and these needs are autonomy, competence, and relatedness. In the context of technology mediated learning, AI systems might potentially contribute to increased autonomy via personalised learning pathways, competence development via adaptive scaffolding and instant feedback and relatedness via collaborative learning capabilities and social comparison processes. The Expectancy-Value Theory, which has been put forward by Eccles and Wigfield, bases its assumptions on the fact that achievement related choices and performance are mainly guided by the expectancies of success that people develop about various tasks and areas and the subjective value that they accord to them. According to this framework, AI-enhanced learning environments have the potential to motivate both expectancy elements by the means of features which generate confidence and exhibiting progress and value elements by the means of relevancy enhanced personalization and goal setting mechanisms which anchor learning activities to individual interests and professional ambitions.

A thorough review of the literature available shows that there are a number of gaps studied in this research. One, AI has been practically applied in virtually every education research project, but has rarely been empirically investigated and its outcomes in education and motivation. Second, the outcome-focused research is heavily underrepresented in the literature regarding education and teacher preparation programs, where the AI applications were developed to a greater extent, and the impact of STEM disciplines is represented significantly by the existing engineering research. Third, the existing research is usually conducted on single-use AI interventions like individual adaptive learning programs/chatbots and not on the combined AI ecosystems that represent simultaneous integration of several technological methods. Fourth, sustained effects are seldom examined by longitudinal studies over a number of academic terms and most studies are single course based or short-term experimentality based. Fifth, methodology weaknesses permeate the current literature such as small sample size that does not allow to conduct strong statistical analysis, lack of better control groups or comparison with behaviors and performance data, excessive reliance on self-reporting measures that could be not triangulated with behavioral or performance data, and insufficient consideration of potential confounding variables such as previous experience with technology or level of motivation. Sixth, a dearth of theoretical grounding is non-experiential in most research studies in educational technology, and there is not enough a relationship between empirical studies and existent motivational or learning theories. Lastly practically implications to be implemented into scale in real educational environments are underfunded with the majority of studies being undertaken in highly controlled laboratory environments or pilot programs with high levels of technical support that cannot be obtained in real institutional environments.

This is thorough-research that seeks to fill the established gaps with the help of the following specific objectives:

1 To develop and deploy an interconnected AI learning ecosystem that is uniquely designed to be specific to education faculty learning curriculum, introducing the features of adaptive learning system, intelligent tutoring, NLP-driven feedback system, and gamification.

2 To test empirically the effect of the use of AI-based learning environments on education students intrinsic and extrinsic motivation using valid psychometric measures, longitudinal and semester 3.

3 To analyze alterations in the learning behaviors such as engagement measurements, persistence measurements and help-seeking patterns in the form of an in-depth learning analytics which will be recorded in the AI system.

4 To examine meditating and moderating variables that affect the connection between the use of AI systems and learning outcomes such as the technology self-efficacy, academic performance in the past, and demographic factors.

5 To understand the experiences of students in the subjective form, subjective perceptions, and meaning-making processes by utilizing the qualitative inquiry methods to offer adequate contextual insights to the quantitative results.

This study contributes to the education research and practice in several ways. Theoretically, the research applies self-determination theory and expectancy-value theory to the study of technology-mediated learning settings with beneficial results in persuading the psychological mechanisms of action by AI systems in the target of motivation. Methodologically, the study has rigorous mixed methods techniques suitable in complex educational technology intervention such as advanced statistical modeling techniques and step-by-step qualitative analysis processes. Empirically, the research has solid evidence on the role of AI, in particular in the context of the faculty of any educational establishment, which is a significant gap in previously published literature. In practice, the results provide practical information that can be used by curriculum developers, education technologies experts, by the faculty members, and the administrators who want to introduce AI-enhanced learning systems. Lastly, the study provides to the wider discussion of educational innovation, incorporation of technology and training teachers on how to operate in technology-based teaching settings.

2. Methodology

In this study, an all-inclusive mixed-methods convergent parallel design was adopted, which gathered and analyzed both quantitative and qualitative data and presented a strong and triangulated evidence of the effects of AI in learning and motivation among education faculty students. The approach of methodology was meticulously created to help curb the drawbacks that are eminent in current research on the educational technology and ecological validity in the manner that the approach is applied in the real learning environment.

2.1 The components of AI Learning Ecosystem

There were four main technological parts of the integrated AI learning ecosystem that addressed the particular pedagogical goals. Adaptive learning platform made use of machine learning algorithms to evaluate performance patterns, knowledge gaps, and learning preferences of each student and adjusted the contents of learning dynamically in regard to their difficulty, sequencing, and form of presentation. The system used the collaborative filtering approaches and the content-based recommendation systems to recommend individual learning input materials such as readings, videos, interactive simulations and practice exercise. The intelligent tutoring system was an on-demand support of a complex educational concept in that it used the natural language understanding as a way of interpreting the queries of students and creating suitable contextual explanations. The system kept highly detailed student models that monitored conceptual understanding, common misconception and preferred style modalities of the explanation that allowed more and more individualized tutorial interactions the longer the systems had existed. The scaffolding systems automatically controlled the level of complexity of the explanation and gave hints before showing full solutions with a gradual mode of presentation.

The feedback systems with the use of natural language processors evaluated student written submissions in different aspects such as the content accuracy, quality argumentation, evidence integration, and academic conventions compliance. In the system, formative feedback was given instantly to indicate special strengths and weaknesses and the revision ideas were linked with applicable teaching materials. The features of sentiment analysis established the emotional tone in discussion posts and written reflections and allowed the intervention of the instructor in advance in those cases when the students demonstrated frustration and lack of interest. Elements integrated in gamification included achievement badges, experience points, visualization of progress, leaderboards and collaborative challenges since they were aimed at establishing intrinsic motivation based on autonomy, competence, and support of relatedness. The system of achievement was able to reward different accomplishments such as mastering of contents, persevering during difficulties, peer support, and metacognitive reflections rather than solely basing on the metrics of competitive performance which may harm intrinsic motivation.

2.2 Data collection instruments

Instruments used in data collection will depend on the problem being studied and the sample used to represent the complete population of the investigation.

2.2.1 Quantitative Measures

Academic Motivation Scale

The validated Academic Motivation Scale was executed at three intervals of assessing intrinsic motivation, identified regulation, introjected regulation, external regulation and amotivation on a 28 items rated scale on a 7-point Likert scale. The instrument had good psychometric specifications with Cronbachs alpha coefficients of between 0.83 and 0.91 among the various subscales in the sample under consideration.

Indicators of Learning Engagement

Behavioral aspects of learning engagement were measured by learning analytics that were automatically generated by the AI system in the form of the duration of time spent, the frequency of resource use, the percentage of assignments and help-seeking actions. The emotional engagement was assessed using the modified Utrecht Work Engagement Scale which was used in a schooling setting and the questionnaire evaluated the dimensions of vigor, dedication, and absorption. Cognitive engagement was accepted by the help of the metacognitive awareness inventory in terms of strategies of planning, monitoring and evaluation.

Academic Performance Measures

A number of performance measures were gathered that were such as the course examination scores, assignment grades, cumulative course grades and where possible results of the standardized assessment. The analytics of the AI systems offered a detail performance data of certain learning objectives and cognitive abilities groups. The results were compared to determine performance gains by comparing the baseline measurements of pre-intervention measurements to the summative assessment of the end-of-semester where initial knowledge summary was incorporated.

Technology Self-Efficacy Scale

It was used to measure technology-related self-efficacy and a 15-item scale was used that measured confidence in using different educational technologies, solving technical issues and moving technology into learning activities. The scale was characterized by high internal consistency of Cronbach alpha of 0.94.

2.2.2 Qualitative Data Sources

A purposely chosen subsample consisting of participants with the maximum variation of demographic features, academic achievements, and the levels of involvement in the AI system were the participants of the semi-structured interviews. The interview protocols involved investigating the experiences of AI learning tools by students, the perceived effects on motivation and learning and the difficulties, as well as recommendations to improve the situation. Semi-structured groups of participants were held at the midpoints and the end of the semesters, and resulted in intensive discussion on shared experiences, social dynamics of learning with AI, and issues that emerged that were not expected during individual interviews. There were focus groups, which were full in participation, with students. The research assistants conducted the focus group discussions guided by the standardized protocols and video recorded the discussions to capture the non-verbal communication and group interaction patterns.

The survey data collected in anonymous open-ended forms at various times requested students to explain what specific cases they encountered when AI tools were used to affect their learning or motivation, what problems were noticed and how the systems could be improved. These written returns proved to be a convenient gathering of qualitative data of the larger sample though acting as a complement to interview and focus group data. As a part of its procedures, statistical analysis will be used to examine the data collected during the study.

2.3 Statistical Analysis Procedures:

The analysis of the quantitative data involved the usage of statistical methods that could be applicable to various research questions and data layout. Early investigations also encompassed descriptive statistics, distributional tests, patterns of missing data and assumption tests that were to be used in the proposed inferential investigations.

2.3.1 Structural Equation Modelling.

The theoretically-based hypothesized relationships to test were the issues of engagement of AI systems, levels of psychological needs, motivation quality, and learning outcomes using structural equation modeling. The proposed model theorized AI involvement as an exogenous factor that determines three mediating ones that are autonomy, competence, and relatedness satisfaction. These mediators then made predictions of intrinsic motivation as well as motivation constructs that consequently had effects on the academic performance and persistence outcomes. Measurement model defined the interrelationships of indicators with latent measures that enabled the measurement of the convergent and discriminant validity. Confirmatory factor analysis measured the model fit before the structural relationships were examined. Maximum likelihood using robust standard errors was used as the model estimation to tackle non-normality of certain variables. Several fit tests were tested such as chi-square test, comparative fit test (CFI), the Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR).

The structural equation model may be mathematically presented like:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{1}$$

where η represents the vector of endogenous latent variables, ξ represents exogenous latent variables, B is the matrix of coefficients relating endogenous variables to each other, Γ is the matrix of coefficients relating exogenous to endogenous variables, and ζ represents structural disturbances. The measurement model is specified as:

$$y = \Lambda_y\eta + \varepsilon \tag{2}$$

$$x = \Lambda_x\xi + \delta \tag{3}$$

where y and x are vectors of observed endogenous and exogenous indicators, Λ_y and Λ_x are factor loading matrices, and ε and δ represent measurement errors.

2.3.2 Hierarchical Linear Regression Analysis

The hierarchical multiple regression was used to analyze the distinctive difference in the learning results that could be explained by the involvement of the AI systems, having excluded the impact of the appropriate covariates. The input of the variables was made on theoretically-justified blocks. Block 1 contained demographic control variables such as gender, age, race-ethnicity, and the level of the program. Block 2 included control academic achievement and previous technology self-efficacy. Block 3 had measures of engagement with AI systems as total time spent on the system, breadth of feature use, and rates of adaptive learning pathways.

The hierarchical regression will be model specified in the following manner:

$$Y_i = \beta_0 + \beta_{1X_{1i}} + \beta_{2X_{2i}} + \dots + \beta_{kX_{ki}} + \varepsilon_i \tag{4}$$

where Y_i represents the outcome variable for individual i, X_1i through X_ki represent predictor variables, β_0 is the intercept, β_1 through β_k are regression coefficients, and ε_i represents the error term. The change in R-squared between nested models was evaluated using F-test.

2.3.3 Repeated Measures ANOVA

Analysis Repeated measures analysis of variance was used in creating changes in motivation across the three measurement occasions. The within subjects' factor was time which had three levels of reference to the beginning, middle, and end of semester testing. Factors between subjects were level of program and level of AI engagement (low, moderate, or high through tertile divides of utilization measures).

$$SS_{total} = SS_{between} + SS_{within} \tag{5}$$

$$SS_{within} = SS_{time} + SS_{error} \tag{6}$$

The test of homogeneity of transparency assumption performed by Mauchly was homogeneity of variance. Where the assumption of sphericity was breached, degrees of freedom were used by Greenhouse-Geisser correction. Partially eta-squared reported the effect sizes:

$$\boldsymbol{\eta_p^2 = \frac{SS_{effect}}{(SS_{effect} + SS_{error})}} \tag{7}$$

2.3.4 Moderation Analysis

The effects of moderation were analyzed for samples to construct conditional effect confidence intervals with bias correction. Potential moderators of AI engagement and learning outcomes were technology self-efficacy and prior academic achievement that were used to test the relationships between them. The important interaction was investigated by looking at simple slopes at the representative values of the moderator variables.

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 (X \times M) + \varepsilon \tag{8}$$

where Y represents the outcome, X is the predictor, M is the moderator, X×M represents the interaction term, and β3 indicates the moderation effect.

2.4 Qualitative Analysis Procedures

Thematic analysis methodology orientation was used in qualitative data analysis that employed systematic procedures. Transcripts of the interview and focus groups were imported to qualitative data analysis programs that help to organize, code and write memos. The overall process of the analysis was conducted in several iterative steps such as familiarization by reading repeatedly, creation of first codes, searching of themes, going through the themes, defining and naming of themes and generating the analytical narrative. The early types of coding involved deductive codes based on theoretical framework, as well as on research questions and inductive codes which were created on the basis of patterns present in the data. One of the coders was a sub-coder who analyzed a subset of transcripts with a different coder to determine the reliability of coding with the results being Cohen kappa of 0.87 which is considered a high level of inter-rater agreement. This was achieved by discussing and agreeing on areas of discrepancy. Pattern coding involved finding relationships between starting codes and subsequently broad units of theme development were to be made. The negative case analysis was the active search of the disconflicting evidence and the alternatives. Member checking was the process of discussing preliminary results with sub groups of participants in order to confirm meanings as well as to create room to elicit further meanings. The themes were analyzed in comparison across the various data sources such as interviews, group discussions and open ended survey responses through analytical triangulation to increase believability of research.

2.5 Integration of Quantitative and Qualitative Findings

The phase of integrating of the mixed methods took place on the increase of interpretation by way of comparison and synthesis of the quantitative findings and the qualitative themes. During the systematic comparison of the quantitative results, joint displays matrices made it easier to compare the results with corresponding qualitative themes. Meta-inferences were constructed by discovering the areas of convergence, complementarity and discordance of quantitative and qualitative strands. The credibility of conflicting areas led to further interpretations to appreciate the explanations.

3. Results and discussions

In Table 1, the descriptive statistics of the important variables of the study in three occasions of measurements are provided. Intrinsic motivation showed significant variations in the baseline to final measurement and amotivation showed the variations in the opposite direction. Models of academic performance also got better during the period of the study. The metrics of AI system engagement levels showed that among the participants there was a significant range of engagement, with average time spent engaged with the AI system amounting to 2.4-18.7 hours per week and the amount of the feature usage ranging between having the simplest adaptive learning functions available to playing with the whole ecosystem.

Table 1. Descriptive Statistics for Key Variables Across Measurement Occasions

Variable	Time 1 M (SD)	Time 2 M (SD)	Time 3 M (SD)	Range	α
Intrinsic Motivation	4.23 (1.18)	5.14 (1.09)	5.70 (0.97)	1-7	.89
Identified Regulation	5.01 (1.24)	5.56 (1.11)	5.89 (0.98)	1-7	.86
External Regulation	5.34 (1.15)	4.92 (1.21)	4.48 (1.28)	1-7	.83
Amotivation	3.12 (1.34)	2.45 (1.28)	1.98 (1.19)	1-7	.91
Academic Performance	78.4 (11.2)	84.7 (9.8)	88.1 (8.4)	0-100	—
Learning Engagement	3.87 (0.94)	4.52 (0.81)	4.89 (0.73)	1-6	.87
AI Usage Hours/Week	—	8.7 (4.3)	9.2 (4.6)	2.4-18.7	—
Tech Self-Efficacy	6.84 (1.92)	7.45 (1.73)	7.89 (1.54)	1-10	.94

Note. N = 487. M = Mean, SD = Standard Deviation, α = Cronbach's Alpha reliability coefficient. Academic Performance represents percentage scores on course assessments. AI Usage Hours were not measured at Time 1 baseline.

Correlation tests indicated study variables with theoretically-consistent relationships. These engagements with AI systems showed moderate positive correlations with intrinsic motivation (r =. 48, p=.001), learning engagement (r=.52, p=.001) as well as academic performance (r=.44, p=.001). These correlations have been preserved when two longitudinal targets were used to analyze relationships between Time 2 AI usage and Time 3 outcomes with control of Time 1 pre-testing measures indicating that there may be causal effects.

3.1 Structural Equation Modeling Results

The theorized structural equation model yielded an acceptable fit to the data observed (kh 2 = 847.32, df = 412, p <.001; CFI =.94; TLI =.93; RMSEA=.046, (90% CI 0.041,051); SRMR =0.052). All the factor loading were more than.60 and significant (p < .001) and this supported convergent validity of measurement model. Square roots of average variance extracted were found to show discriminant validity which is superior to inter-construct correlations.

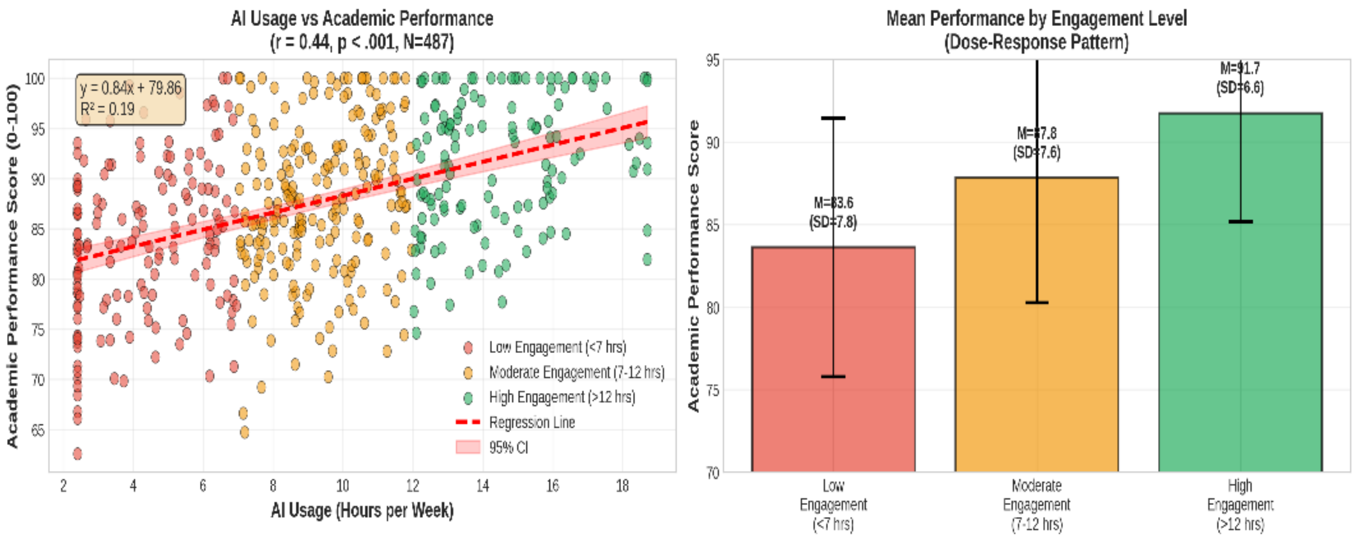

Fig 1: AI Usage vs Academic Performance

Table 2 includes the results of standardized path coefficients of structural relationship. The involvement of AI systems had a great contribution with positive impacts on the three variables of psychological need satisfaction. The competence need satisfaction (β =.52, p <.001), autonomy need satisfaction (b =.41, p <.001), and relatedness need satisfaction (β =.34, p <.001) were found to have the strongest influence. Such results indicate that AI learning settings were especially helpful during the students to experience the sense of effectiveness and mastery as well as endorse self-directed learning and social interaction.

Table 2. Standardized Path Coefficients from Structural Equation Model

Structural Path	β	SE	t-value	p-value
AI Engagement → Autonomy	.41	.052	7.88	< .001
AI Engagement → Competence	.52	.048	10.83	< .001
AI Engagement → Relatedness	.34	.056	6.07	< .001
Autonomy → Intrinsic Motivation	.38	.054	7.04	< .001
Competence → Intrinsic Motivation	.47	.051	9.22	< .001
Relatedness → Intrinsic Motivation	.29	.058	5.00	< .001
Intrinsic Motivation → Performance	.36	.055	6.55	< .001
Intrinsic Motivation → Persistence	.43	.052	8.27	< .001

Note. β = Standardized path coefficient, SE = Standard error. All paths significant at p < .001. Model fit indices: CFI = .94, TLI = .93, RMSEA = .046, SRMR = .052.

Based on the intrinsic motivation, there was significant positive correlation between the two variables that are; psychological need satisfaction with competence (b = .47, p < .001), autonomy (b =.38, p <.001) and relatedness (b =.29, p <.001). Lastly, intrinsic motivation was found to positively anticipate academic performance (b = .36, p <.001), as well as, learning persistence(b =.43, p =.001). These results are a substantial indication that the theoretical model based on the possibility that AI learning setting promotes the motivational process of fulfilling psychological needs, which in turn promotes the positive learning results, is well implemented.

Sanctioned bias-corrected bootstrap confidence intervals, (10,000 resamples) were used to determine the indirect effects. The overall mediated impact of AI interaction on intrinsic motivation using the three mediating elements of need satisfaction variables was also substantial (b =.49, 95% CI (.42, .57), p < .001). Specific indirect effects showed that all directions showed a significant contribution to it, though competence (b = .24, 95%CI (.19, .30)) and autonomy (b =.16, 95%CI (.11, .21)) have the greatest contributors to the contribution. These results indicate that, although all three needs of psychology are significant, competence need satisfaction is the main pathway in which an AI learning setting can increase intrinsic motivation.

3.2 Hierarchical Regression Analysis Findings.

Table 3 displays an analysis of hierarchical regression that evaluates the predictors of outcomes based on academic performance. The Model 1 which involved demographic control variables alone explained 8.4% of the academic performance (F(5, 481) = 8.84, p <.001). There were small but significant effects on gender, level of the programs, and race-ethnicity where female students and graduate students had small, yet significant performances. Model 2, which included baseline achievement, and technology self-efficacy, contributed significantly more to the explained variance of 31.7% (DR2 =.233, F (2, 479) = 82.46, p <.001). The strongest predictor became Academic achievement of other academic achievements (b =.42, p < .001) in line with the other multiple studies carried out on education that showed the relevance of prior knowledge.

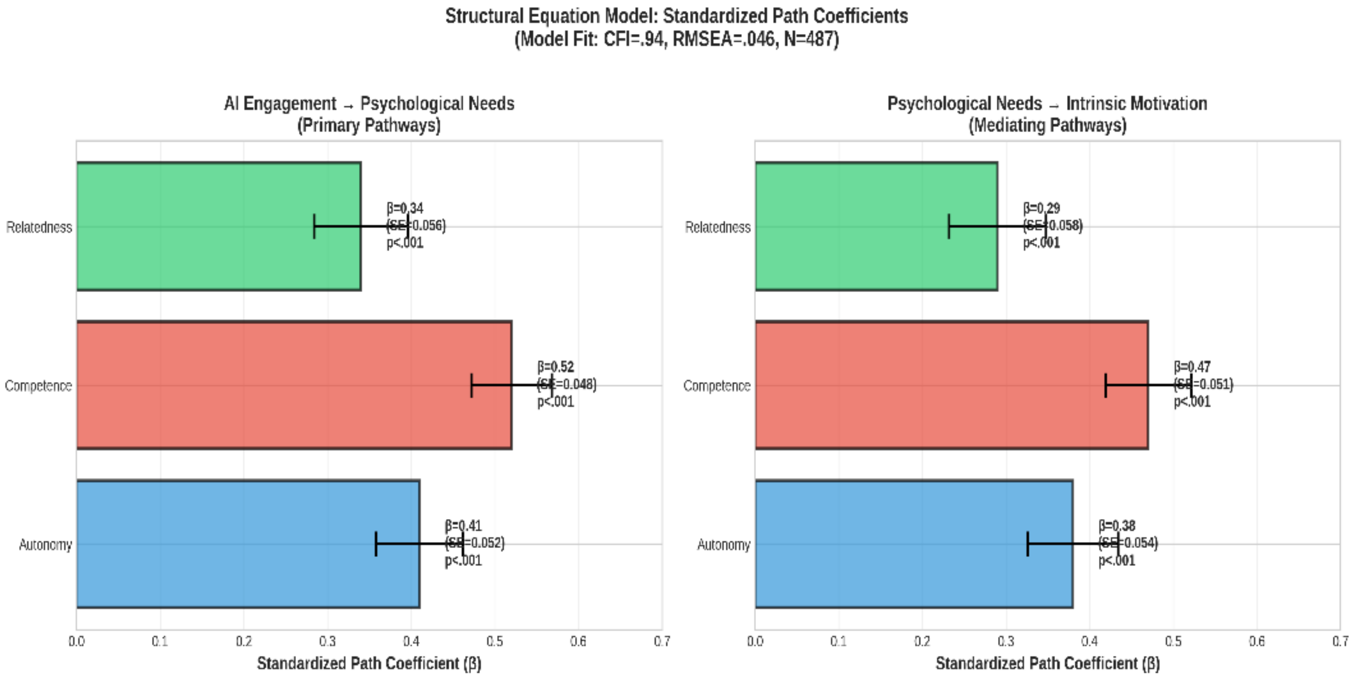

Fig 2: Structural Equation Model Path Diagram Visualization

Table 3. Regression Analysis Hierarchy to Predict Academic Performance.

Predictor	Model 1 β (SE)	Model 2 β (SE)	Model 3 β (SE)	R^2	ΔR^2
Gender	.14** (.042)	.09* (.038)	.07 (.036)	.084	—
Age	.06 (.045)	.04 (.041)	.02 (.039)		
Program Level	.11* (.043)	.08 (.039)	.06 (.037)		
Baseline Achievement	—	.42*** (.038)	.35*** (.036)	.317	.233***
Tech Self-Efficacy	—	.15*** (.040)	.10* (.038)		
AI Usage Hours	—	—	.28*** (.037)	.447	.130***
Feature Utilization	—	—	.19*** (.038)		

Note. N = 487, β = Standardized regression coefficient, SE = Standard error, p = p <.05, p =p under.01, p = p under.001.

Model 3 with the addition of measures of AI system engagement enhanced explained variance gradually to 44.7% (DR 2 =.130, F(2, 477) = 55.84, p <.001). The AI utilizations time (β = .28, p < .001) and breadth of feature use (β = .19, p <.001) also had significant predictive value on academic performance over all the predictors. These results prove that the involvement of AI has a significant amount of individualized variance in academic performance beyond the effects of the demographic factors, previous achievement, and technology self-efficacy. The size of AI engagement effect was in line with the size of the effect of baseline achievement, which implies that the effect of AI engagement on student learning has practical values.

3.3 Repeated Measures Analysis Results

Table 4 shows repeated measures ANOVA that examine change in motivation between the three occasions of measurements. According to the test done by Mauchly, there was violation of assumption of sphericity (W =.89, p =.008) and therefore greenhouse Geisser corrected results are provided. The main effect of time within subjects was significantly high (F (1.87, 908.42) = 124.67, p < .001, η²_p = =.204), which showed the presence of significant changes of intrinsic motivation through the semester. Paired t-tests of Time 1 vs Time 2, and Time 2 vs Time 3 with Bonferonni corrections have found significant increases in Time 1 vs Time 2, Time 2 vs Time 3 (MD = 0.91, SE = 0.065, p < 0.001), and Time 3 vs Time 2 (MD = 0.56, SE = 0.058, p < 0.001).

Table 4. Repeated Measures ANOVA Results of Intrinsic Motivation.

Source	df	F	p	η^2_p
Within-Subjects Effects				
Time	1.87, 908.42	124.67	< .001	.204
Time × AI Engagement Level	3.74, 908.42	8.94	< .001	.036
Time × Program Level	1.87, 908.42	2.14	.121	.004
Between-Subjects Effects				
AI Engagement Level	2, 481	43.72	< .001	.154

Note. The values of N = 487 and df = degrees of freedom (corrected by Greenhouse-Geisser) and e2p = partial eta-squared effect size were obtained.

The interaction between Time x AI Engagement Level also highlighted (F (3.74, 908.42) = 8.94, p <.001, η^2_p = .036) a difference of motivational change according to the degree of AI system engagement. Simple effects analysis indicated that large effect sizes in baseline to midpoint (MD = 1.24, p <.001) in high AI engagement students were noted as compared to moderate (MD =0.87, p <.001) and low engagement students (MD = 0.54, p <.001). It was a similar trend in between midpoint and endpoint with high engagement students recording significant further gains (MD = 0.71, p <.000) and low engagement students recording insignificant changes further (MD = 0.28, p =.042). These results are indicative of the dose-response relationship whereby, the higher the AI involvement, the higher motivational gains.

3.4 Results of the Moderation Analysis

The moderation analyses investigated the hypothesis of the existence of differences in relationships between AI engagement and learning outcomes as a function of technology self-efficacy and previous achievement. The results of a moderation model are provided in table 5. The technology self-efficacy mediated the connection between time spent on AI use and achieved academic performance significantly (b = 0.18, SE = 0.056, t = 3.21, p =.001, 95% CI (0.07, 0.29)). This was indicated in the simple slopes analysis, which found the positive correlation related to performance was stronger between students with high technology self-efficacy (b = 0.46, SE = 0.081, p < .001) than either with moderate (b = 0.31, SE = 0.058, p =.072) or low self-efficacy (b = 0.15, SE = 0.083, p =.072). According to this trend, students with high confidence in the usage of technology were in a stronger place to utilize AI learning tools to their advantage.

Table 5. Moderation Analysis Results Predicting Academic Performance

Predictor	b	SE	t	95% CI
Model 1: Tech Self-Efficacy as Moderator				
AI Usage Hours	0.31	0.058	5.34	(0.20, 0.43)
Tech Self-Efficacy	0.24	0.062	3.87	(0.12, 0.36)
AI Usage × Tech Self-Efficacy	0.18	0.056	3.21	(0.07, 0.29)
Model 2: Prior Achievement as Moderator				
AI Usage Hours	0.29	0.061	4.75	(0.17, 0.41)
Prior Achievement	0.38	0.054	7.04	(0.27, 0.49)
AI Usage × Prior Achievement	-0.14	0.059	-2.37	(-0.26, -0.03)

Note. N = 487. b = Unstandardized regression coefficient, SE = Standard error, CI = Confidence interval.

On the other hand, the previously attained success showed a negative moderation effect (b = -0.14, SE = 0.059, t = -2.37, p =.018, 95% CI=0.44241). The advantages of AI-engagement to students were highest in lower-achieving students (b = 0.42, SE = 0.087, p =.001), middle-achievers (b = 0.29, SE = 0.061, p =.031), and smallest although significant in high-achievers (b = 0.17, SE = 0.079, p =.031). This compensatory trend implies that AI learning settings have the potential to decrease the achievement disparity due to the provision of students who come in with weaker academic performances with especially valuable assistance.

3.5 Qualitative Findings

Interpretative analysis of the study through the use of thematic analysis of Interview, focus group and open-ended Survey data generated five broad themes summarizing the experience of the students with AI-enhanced learning environments. The themes will help to develop a comprehensive contextual insight that will offer a complementary quantitative data and expose subtle insights into the issues of implementation and factors of success.

3.5.1 Theme 1: Change of the Self-Efficacy and Competence Perceptions

The participants in the study repeatedly reported core changes in their confidence concerning the academic skills and the ability to integrate technologically [29-32]. The explanation of one of the graduate students is the following: The adaptive learning platform gave me the understanding that I could actually master the statistical concepts, which I had always considered to be beyond my abilities. It has divided it into small manageable bits and it has been hailing me on the way, which has entirely reformed my thinking process regarding what I was able to achieve. Such change was observed among students especially those who registered courses with mathematical anxiety or technological fear.

According to most students, the increased confidence was not restricted to the course material, but rather reflected on the self-efficacy in teaching. One of the elementary education majors at the undergraduate level wrote: 'The tasks I performed on these AI tools opened my eyes that it is possible to become the type of teacher who successfully applies technology in her classroom. Prior to this, I always envisioned myself to be the type of individual who was not going to go beyond the conventional approaches, as the new technology looked too complex. I am now prepared and ready to make something of it. This result implies that AI learning experience can lead to the benefits not only related to short-term academic results but also to career preparation and development of professional identity.

3.5.2 Theme 2: Individualization and Autonomy-Supportive Learning.

Students stressed the importance of the individuality of AI-based education, especially, the possibility to study at personal pace and pay much attention to aspects that demand extra attention [31,33-35]. One of the education majors at middle schools elaborated: The system had realized that I could know certain concepts very well but not others. That appreciation of my personal learning requirements helped to make me considerably more involved.

Nevertheless, other students were worried of the high levels of personalization that might hamper the chances of group learning and exposure to varied views [36-38]. One of them commented: 'Although I enjoyed the option of doing work at my own speed, I occasionally found myself missing the discussions that we would have had in a more conventional classroom where everybody was studying the same material, simultaneously. These remarks represent a conflict between individualization advantages and possible expenses in the terms of social learning possibilities.

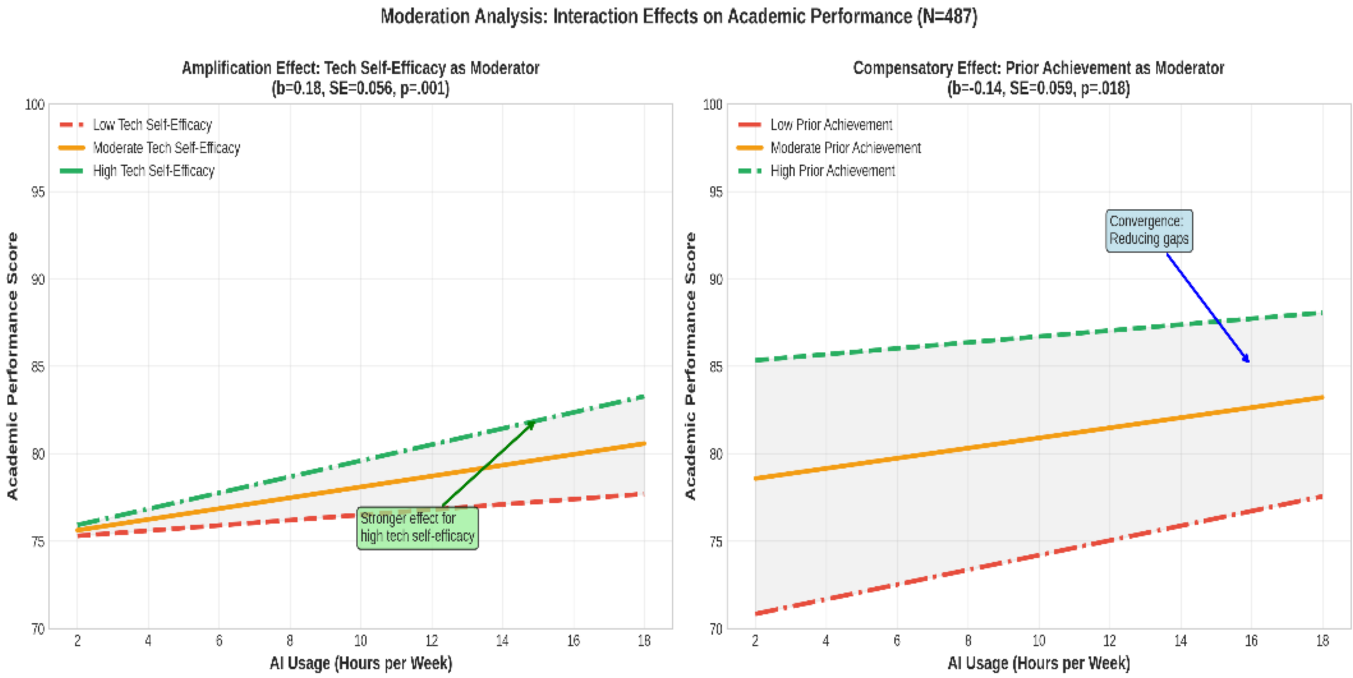

Fig 3: Moderation Effects - Interaction Visualizations

3.5.3 Theme 3: Instant Feedback as an Inspiring Engine.

The instantaneous essence of AI-generation feedback proved to be an important driving force [1,39-41]. Students explained the role of instant feedback in letting them create and apply improvements quickly after they found something wrong about their work, which could not be done with them. One of the graduate students who majored in instructional design has said: I could get feedback only a few seconds after sending a draft and that was the time when I could make changes and ideas remained in my head. Such responsiveness made me interested and encouraged me to continue to better the job instead of simply turning in something and move on. Besides, students enjoyed AI feedback being less evaluative threat as compared to instructor feedback. One of the students, who is an undergraduate, said: The process of providing feedback by the AI system to me did not make me feel evaluated or ashamed of errors. I would be able to test things and make mistakes without fear of being judged by my professor on what I was like.' The finding indicates that AI feedback can alleviate the evaluation anxiety which makes learning less active at times.

3.5.4 Theme 4: Gamification Aspects and Self-Motivation.

Gamification features caused mixed reactions and efficiency seems to heavily be based on implementation factors and personal preferences [42-44]. Most learners claimed that badges of achievement, displays of progress and challenge modes turned normal learning processes into entertaining ones. One secondary education major added: The achievement system made the process of studying really fun rather than merely something that I had to get through and do. I was also competing against my past scores and work towards all the badges and that is what made me repeat to practice even when I was not technically supposed to. Nevertheless, other students were worried that the problem of competition might negatively affect the intrinsic motivation because the attention might be shifted to the social comparison instead of the mastery over the self. One respondent described it as follows: 'Being ranked in the lower part of the leaderboard, on the contrary, made me less motivated. I began to be concerned about the comparisons with other people rather than concentrate on my learning objectives. Such opposite responses implement the lesson of considering the implementation of gamification features.

3.5.5 Theme 5: Implementation Problems and Barrier to technology.

Some of the implementation challenges that were found to interfere with optimality in learning among students were identified [45-46]. Malfunctioning of the system in the form of glitches, slow loadings, and some mistaken AI behaviors brought some frustration, which slowed down the involvement, but only temporarily. One of the graduate students reported: The system of intelligent tutoring confirmed me wrong on a critical concept, and it affected my trust; as I now doubted the system which I would use in the future. The doubt of that discouraged me.' Also, the students pointed out that the effective introduction of AI was predetermined by proper orientation and the continuous assistance. The respondents who were thoroughly trained and could access technical support whenever they needed were more positive and engaged in a process than individuals who experienced difficulties in figuring out the features of the systems on their own.

3.6 Integrated Discussion

The combination of quantitative and qualitative technologies adds up to a complex yet finally encouraging situation with the potential of AI in facilitating learning and motivation in the atmosphere of education faculty students [18,47-49]. The outcomes of the structural equation modelling support significantly the theoretically-based mechanisms and show that the AI learning environments appear to elevate motivation by following the psychological need pathways. Qualitative themes that highlight transformative impact on self-efficacy and confidence is in accordance with the finding that the competence need satisfaction was found to be the strongest mediator. The hierarchical regression and repeated measures ANOVA findings report some significant practical effects of engaging in AI on academic achievements. The 13 per cent gain in explained variance studies through AI engagement measures are related to real world impacts since the model already in the control for the strong predictors such as previous achievement and technology self-efficacy. The dose response relationships that can be observed in repeated measures results imply that the promotion of persistent and intensive use of AI learning tools can optimize the advantages.

The results of moderation present valuable information on the issue of equity. The compensatory effect of the previous achievement suggests that the AI learning settings can contribute to minimizing instead of deepening achievement gaps, and bring most benefits to the students who require further support most. The trend is a direct opposite to fears that educational technology only benefits those students who have been privileged. Nevertheless, the effect of technology self-efficacy moderation implicates the fact that it is not enough to just offer the AI tools and leave the student to build confidence and use the tools independently of becoming competent in it. The qualitative insights shed light on reasons that support an effective implementation of AI. The motif on immediate feedback as a driving force should be used to interpret quantitative results by clarifying particular processes that make AI systems more appealing and efficient in remote interaction and encouraging adherence. According to the descriptions that students gave concerning the possibility to repeat the same task swiftly with little or no anxiety about evaluation, AI feedback could be especially helpful in the development of psychologically safe learning environments in which experimenting and risk-taking are desirable behaviors to be promoted.

The issues of implementation that have arisen in the qualitative results bring an actual sense of direction to institutions that may contemplate the use of AI. The necessity to be thoroughly trained, have a sound technical backbone and have lifelong support cannot be emphasized more than it is. Pedagogically advanced AI technologies will not bring desired outcomes when students fail to access them, or do not feel safe and secure to use it efficiently. The above results show that effective integration of educational technologies is not a matter of purchasing the technology but significant investment in professional development, technical and user-experience optimization.

4. Conclusion

This is a thorough research that quotes a solid empirical data that well-planned and deployed artificial intelligence learning ecosystems could lead to a significant improvement in the learning outcomes as well as motivation among faculty students in education. Based on three semesters of rigorous mixed-methods research involving complex statistical modeling and deep qualitative investigation, this research presents significant changes in various outcome dimensions and sheds some light on the psychological mechanisms and situational aspects that are important in effectiveness. Statistically significant and practically significant effects of AI engagement on intrinsic motivation, learning engagement, and academic performance were statistically found in quantitative analyses. The structural equation modeling revealed that AI systems build motivation based on the psychological need satisfaction processes, and all three needs namely, competence, autonomy, and relatedness needs had significant positive associations with system engagement. The fact that competence need satisfaction was the most effective mediator implies that AI learning conditions are especially good at the development of student confidence and self-efficacy based on adaptive scaffolding, real-time feedback, and successive experiences of mastery.

Hierarchical regression investigations also reported that AI involvement added significant specific variance to academic performance on top of demographic, prior achievement and technologies self-efficacy. The 13 percent increase in the explained variance of the AI metrics is of some practical importance. Repeated measures analysis suggested continued motivational gains throughout the semester with students highly engaged showing especially strong gains. These longitudinal results overcome shortcomings of previous studies which have only analyzed limited outcomes which are short term and proposes that the benefits of AI are not always diminished over the years. The moderation analyses provided recommendations with significant equity overtones. The compensatory effect of previous accomplishments shows that AI learning contexts have the most significant advantages to those who came with poorer academic backgrounds, meaning that it may decrease but not increase achievement gaps. Nonetheless, the amplification effect of technology self-efficacy emphasizes that it is not enough to offer AI tools and make sure that every student gains the confidence about his/her ability to use it successfully.

The qualitative findings provided a sense of enrichment to quantitative findings since the results indicated the lived experiences of the students, the processes of making meaning, and views of the students towards AI learning tools. There were five dominant themes with change of the self-efficacy perception, valuing personalized autonomy-supportive learning, external stimulus, which is immediate feedback, ambivalent response to gamification as simulated, and several issues about the implementation, which needed to be addressed. These themes offer insightful information regarding the reasons and how AI systems affect motivation and what factors can help it be successful or hinder success. This study contributes to the theory in a number of ways. To start with, it offers solid empirical evidence of the self-determination theory in technology-mediated learning procedures, showing that mechanisms of psychological needs satisfaction under AI-enhanced situations are similar to those under traditional methodology instructions. The fact that all three fundamental psychological needs are predictors of an intrinsic motivation according to their expected directions legitimizes the theoretical framework and at the same time broadens the applicability to the present-day educational technologies.

Second, the study can add to the expectancy-value theory through showing how AI learning can improve both expectancy elements via the confidence-inducing property and instant performance feedback and value elements via the personalization and relevance-inducing processes. In particular, moderation results are helpful to understand the limitation cases and personal variation, which can drive AI application most efficiently, which can help to deepen the theoretical research on motivation. Third, the study builds on the research in the area of learning analytics by showing how the granular data of behavioral observations use AI systems can not only shape the theoretical knowledge but also practically contribute to the optimization of the instruction. These dose-response associations found in repeated measures tests indicate that the strength of engagement has significant impacts, and they have their implication on theory and practice in relation to the best implementation strategies. Results present many practical implications of the study to educators, the administration, and educational technology designers. To begin with, AI institutions that invest in learning technologies must put in place all-encompassing ecosystems that incorporate numerous features that are complementary as opposed to individual, distinct tools. Importance of the synergistic effects in this study indicates that adaptive learning platforms which are told with intelligent tutoring, NLP-equipped feedback and well-considered game-based elements yield more benefits when combined together than individually.

Second, effective AI integration will involve heavy investment in the professional staff and students. The instructors should be trained in the pedagogical usage of AI tools, learning analytics interpretation, and approaches to the upholding of the presence of human interaction in the increasingly automated learning setting. The students need to be oriented on the features of the system, given constant technical support, and made aware of metacognitive learning management of self-regulated learning in the technology-rich situations. Third, the design of AI systems must focus on autonomy-related characteristics, such as individualized learning paths, options in the type of content and assessment format, and mastery-oriented components of gamification, as opposed to the competitor-oriented ones. The qualitative results of negative responses to leaderboards can be interpreted to imply that the social comparison processes might negatively affect the intrinsic motivation of certain types of students, which is why much attention should be paid to it, or the students may join the leaderboard as an option.

Fourth, the institutions are to track the trends of engagement and actively assist the students with the low use. The dose-response curves that became obvious during the current study indicate that significant benefits are received by the students who use AI tools intensively. Primary reinforcements of non-participating students and selective interventions that help in dealing with factors hindering participation can be used to maximize gains in full student populations. Fifth, AI deployment needs to have effective measures to assure system reliability, accuracy and responsiveness. Poor technical issues and inappropriate automated feedback may quickly damage the student trust and interest, risking to concentrate on advantages. The Quality assurance measures such as frequent auditing of AI generated content, user experience check actions and responsive technical support infrastructure are all necessary investments.

Although methodological rigor and the scope of this research are extensive, some limitations of this research should be taken into consideration when the results are interpreted. To begin with, the research was carried out in one institution, which may not be applicable to education programs of different demographic profiles, resources and organizational cultures. Recreation in a wide range of institutional settings would build more confidence on the wider applicability. Second, the study tested one particular integrated AI ecosystem; the study results might not be applicable to other technological setups or single AI applications applied singly. The aspects of synergy that were found in this research may be specific to combinations of features that are not similar across systems deployed in different settings.

Third, although the longitudinal study of three semesters is a significant better deal compared to a short-term study, longer study would enhance the understanding of long-term consequences and the possibility of habituation and disillusionment that may be observed during a greater time time. Fourth, the study was not able to use true random assignment of treatment and control condition because of the ethical aspects and institutional limitations. Although statistical controls aided in dealing with potential confounds, quasi-experimental designs do not and cannot disapprove all other explanations as strongly as do randomized controlled trials.

Fifth, even though self-reported motivation scales are validated and popular, they can be influenced by social desirability or low levels of metacognition awareness. The limitation was also mitigated through triangulation with behavioral as well as the conduct of further research through broader application of implicit measures or physiological measures. There are a number of interesting avenues to future researches that are informed by this investigation. To begin with, longitudinal studies that can follow the education students covered by their preparation programs into early career teaching would shed light on the idea of whether the advantages of AI-enhanced learning experiences will be translated into further professional practice. Are students who had learning tools of AI in preparation programs also able to incorporate educational technology better in their respective classrooms? This question would help in giving evidence pertaining to the ultimate influence on K-12 students instructed by AI-prepared teachers.

Second, comparative effectiveness studies involving the investigation on various AI system settings would be beneficial in determining the best design principles. What are the characteristics that have the greatest provisions to motivation and learning results? Is there a special focus on specific characteristics to a specified subset of students or educational goals? The evidence-based design would be informed by systematic exploration of the effectiveness of the components. Third, the study of implementation factors and contexts would contribute to the knowledge about the conditions contributing to effective implementation of AI or hindering it. What works best as policies by the institution, resource distribution, and culture? What is the best way to streamline change management processes to foster technological transition in faculty and students? These questions deal with reality problems that institutions experience when trying to establish innovations beyond pilot projects.

Fourth, relevant questions should be inquired about the possibility of its unintended consequences and even ethics. Do most people concern critical thinking, creativity, or other valuable cognitive abilities because of the high use of AI systems? What is the best way to ensure privacy whilst using learning analytics? What are the barriers to making algorithms perpetuate education disparities? These issues grow more and more pressing as there is an increase in the integration of AI. Fifth, equity implications would be more effectively represented by research studies involving inequity effects on dissimilar groups of students. The present research established compensatory student outcome effects on the low-achieving students, whereas further research is required on other sources of diversity such as racial-ethnicity, social economic status, disability status and English language skills. The realization of the optimization of AI learning environments to help all students equally would be an important study need.

Sixth, the new AI functionality, such as large language models, generative AI, and more advanced natural language processing, presents potential opportunities and challenges that need a systematic exploration. What can be done to harness these potent new technologies by the methods that augment but never supersede human instruction and learning? What does new assessment and evaluation in situations where AI can produce advanced academic activity require? These changing questions shall remain in need of research focus. This in-depth study offers positive affirmations that the application of artificial intelligence has significant promise to positively improve learning and motivation levels among learning faculty and students as a part of the educational institution through careful initiation in evidence-based pedagogic systems. The significant gains in intrinsic motivation, learning interest, and academic scores recorded by both quantitative and qualitative studies indicate that AI learning ecosystems are promising innovations that should receive further improvement and development, as well as strategic deployment.

But discoveries also provide emphasis that it is not enough to use technology. To learn the potential of AI, one needs to pay close attention to such aspects as psychological principles, individual differences, the quality of implementation, the further development of a professional, and self-evaluation. The innovations in educational technology are successful or not, depending on how close they are to the basic human learning processes and their suitability to the realities of the educational settings.

With the continued rapid development of artificial intelligence possibilities, there is a special task of the education faculty programs to prepare the future teachers which can endure in the new technology-saturated teaching conditions efficiently and ethically. Through education students engaging in ideas of AI learning tools in their preparation, the programs could create technological ability and pedagogical complexity to reflect on the application of technology during their teaching sessions in later teaching careers. This twofold advantage of improved preparation results and simulation of efficient technology combination can be viewed as strong arguments supporting the further investment in AI-based teacher training.

Moving ahead, the profession should strike the right balance between technology innovation zeal and adherence to evidence based practice, equity and values of basic education. Artificial intelligence presents a strong potential, but it has to be utilized towards legitimate learning, wellbeing, and social justice. Such balanced, principled integration is given a ground based on this investigation as well as it provides the questions of significance needed to be addressed through further research. The way ahead involves continued partnership of educational researchers, technology developers, daily educators and policy makers who will be determined to take advantage of the potential of AI and preserve what is most important in education nurturing human learning, growth, and prosperity.

Author Contributions

IJM: Conceptualization, writing original draft, writing review and editing. OMN: Conceptualization, study design, analysis, data collection, methodology, writing review and editing, and supervision. NLR: Conceptualization, study design, analysis, writing original draft, writing review and editing, and supervision. JR: Study design, analysis, data collection, methodology, software, resources, visualization.

Conflict of interest

The authors declare no conflicts of interest.

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