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The Role of Artificial Intelligence in Enhancing Learning Motivation, Sports Skills, and Academic Engagement Among Physical Education Students

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Abstract

Artificial intelligence offers new ways to explain course content, personalize practice, and provide feedback in physical education. However, access to an AI tool does not itself establish stronger motivation, better sports performance, or sustained academic engagement. This proposed study will examine associations between educational AI use, learning motivation, self-reported sports skill competence, and academic engagement among physical education students in Punjab, Pakistan. A quantitative cross-sectional survey will target 223 undergraduate students enrolled in physical education or closely related sports sciences programmes at participating institutions located entirely within Punjab. Institutions will be selected to include northern, central, and southern Punjab and both public and private provision; students will then be sampled from institutional enrolment lists. A structured questionnaire will assess AI use during the preceding four weeks, three learning outcomes, technological access, and implementation barriers. Expert review, cognitive interviews, and a separate pilot will precede the main survey. Analyses will include descriptive statistics, assessment of measurement quality, three primary correlations with adjustment for multiple testing, and exploratory adjusted regression models. The study will examine reported associations rather than establish causal improvement. Sports skills will be interpreted as perceived competence because the proposed survey does not include an objective performance test. The design is intended to inform contextually appropriate AI integration and provide a basis for subsequent intervention research in Punjab. A separate statistical demonstration uses 223 synthetic records; its numerical results are illustrative and do not describe actual students.

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Introduction

Introduction

Physical education requires students to connect conceptual knowledge with bodily movement, repeated practice, and reflection on performance. Students must understand why a technique works, recognize errors, and remain engaged long enough to improve its execution. These demands create several possible roles for artificial intelligence (AI), including conversational explanations, adaptive learning activities, and automated analysis of movement. A review of educational AI identifies applications across learning, teaching, assessment, and administration, while also showing that the relationship between a technological application and an educational outcome needs explicit investigation. These distinctions matter in physical education, where answering a theoretical question and performing a practical skill represent different forms of learning (Chiu et al., 2023).

The educational value of AI in this field depends on how it is incorporated into teaching and practice. A conversational system may help a student understand biomechanics or prepare

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revision questions, whereas a computer vision system may identify aspects of movement technique. These functions should not be treated as interchangeable. A physical education review found a small and geographically concentrated evidence base, with studies examining applications such as intelligent instruction and movement analysis. Its findings support further investigation of educational uses while cautioning against broad conclusions about effectiveness across settings (Bofill et al., 2025).

Learning motivation is particularly relevant because the acquisition of sports techniques can involve repeated errors and slow progress. Students may approach a difficult activity with curiosity, personal commitment, external pressure, or little sense of purpose. Self-determination theory explains why these differences in the quality of motivation matter. In this account, learning environments can support autonomy, competence, and relatedness, thereby encouraging more self-endorsed participation. AI feedback could contribute to such conditions when it clarifies a manageable next step and leaves room for student judgement. Its motivational role therefore warrants examination rather than assumption (Ryan & Deci, 2020).

Sports skills and academic engagement require separate attention. A student may find AI explanations helpful without using an AI system during practical training. Similarly, frequent use of a chatbot does not necessarily indicate attentive participation, careful reasoning, or sound movement technique. Research developing the University Student Engagement Inventory distinguishes behavioral, cognitive, and emotional engagement. This multidimensional understanding provides a useful basis for examining whether AI use relates to participation in coursework, thoughtful processing of ideas, and interest in the learning experience (Maroco et al., 2016).

The topic has direct curricular relevance in Pakistan. The Higher Education Commission's revised physical education curriculum includes an interdisciplinary course on AI in physical education and identifies applications in teaching, performance analysis, personalized training, and ethical decision-making. This establishes a reason to investigate students' experiences within the discipline. It does not establish that institutions have implemented the course uniformly or that students already use the same technologies. In Punjab, the present study will investigate those experiences through evidence collected from participating institutions rather than infer implementation from the national curriculum alone (Higher Education Commission [HEC], 2024).

A study confined to Punjab can examine the relationship between educational AI use and learning outcomes within a defined provincial context. It can also document whether students report access to suitable devices, internet connectivity, and institutional support. These conditions will be measured as features of participants' experiences; differences across localities or institutional sectors will not be presumed. The proposed contribution is a consistent account of three educational outcomes alongside actual reported AI practices, with the main sample fixed at 223 students.

Statement of the Problem

Physical education programmes have a curricular reason to engage with AI, but favorable expectations are insufficient grounds for claiming educational benefit. The evidence needed for local decisions concerns what students use AI for, how that use relates to their motivation and engagement, and whether perceived sports competence follows the same pattern. The

present study addresses this problem in participating institutions in Punjab. It will distinguish academic AI use from sports-related AI use and will avoid treating students' confidence in their skills as proof of improved physical performance. The empirical question is whether the proposed relationships are supported within the planned sample, including uncertainty and alternative explanations.

Objectives of the Study

1. To identify the frequency and purposes of educational AI use among physical education students in Punjab.
2. To examine the association between educational AI use and students' learning motivation.
3. To examine the association between educational AI use and students' self-reported sports skill competence.
4. To examine the association between educational AI use and students' academic engagement.
5. To describe technological access and barriers relevant to AI use in participating physical education programmes.

Research Hypotheses

H1: Greater educational AI use will be positively associated with learning motivation.

H2: Greater educational AI use will be positively associated with self-reported sports skill competence.

H3: Greater educational AI use will be positively associated with academic engagement.

The hypotheses specify expected directions, but all primary statistical tests will be two-sided. Negative, negligible, and uncertain associations will be reported alongside positive associations.

Review of Related Literature

Artificial Intelligence in Physical Education

Educational AI encompasses several capabilities rather than a single teaching method. For physical education, an essential distinction concerns systems that work mainly with text and systems that evaluate movement or performance information. A student who requests an explanation of a training principle has a different learning experience from a student receiving automated feedback on a recorded action. The proposed questionnaire therefore separates academic and sports-related activities. This approach responds to the variation in tools and purposes identified in the physical education literature and supports more precise interpretation of any associations (Bofill et al., 2025).

Artificial Intelligence and Learning Motivation

Motivation concerns both the strength and the reasons underlying participation. A meta-analysis of student motivation found different relationships between motivational forms and educational outcomes, with intrinsic motivation and personally valued learning showing particularly useful associations. These findings discourage equating compulsory compliance with sustained interest. In the proposed study, motivation items will focus on curiosity, interest, and perceived value in physical education. They will not ask respondents to agree that AI makes them motivated, because that wording would build the hypothesised relationship into the measurement itself (Howard et al., 2021).

Evidence specific to physical education also supports attention to the learning environment. A systematic review and meta-analysis applying self-determination theory to

physical education linked autonomous motivation with adaptive outcomes and highlighted the relevance of psychological need satisfaction. This provides a theoretical explanation for why understandable feedback, attainable challenges, and supportive teaching might matter. However, the proposed study will not directly measure every psychological need or establish a motivational mechanism. Self-determination theory will guide the interpretation of observed patterns rather than serve as a claim that the full theory has been tested (Vasconcellos et al., 2020).

Artificial Intelligence and Sports Skills

A university yoga study examined a gamified intelligent tutoring and instant feedback system grounded in self-determination theory. It reported benefits for yoga performance, engagement, and need-related experiences. This provides an example of a defined educational intervention with a particular skill domain, rather than evidence that any AI application improves all sports skills. Its relevance to the present research lies in demonstrating the importance of connecting the tool, the instructional design, and the outcome being assessed (Hsia et al., 2025).

A more recent university physical education trial evaluated structured generative AI feedback during basketball instruction and included a delayed assessment without feedback. The study reported advantages for the complete feedback package while cautioning that the design did not isolate an AI-specific contribution from all other differences between conditions. It also distinguished short-term retention from longer-term learning. This helps define the limits of the present survey: reported sports competence can be studied efficiently, but a claim of actual skill improvement would require direct assessment over time (Dong & Zhang, 2026).

Artificial Intelligence and Academic Engagement

Academic engagement is broader than the frequency of accessing a digital service. Behavioral engagement concerns participation and task involvement; cognitive engagement concerns thoughtful processing; emotional engagement concerns interest and connection to learning. The engagement inventory developed for university students provides empirical support for examining these related dimensions. The present study will use newly drafted items informed by this conceptual distinction. These items will require their own evaluation and will not be represented as the original validated inventory (Maroco et al., 2016).

A review and meta-analysis of experimental ChatGPT studies identifies the need to distinguish the quality of AI-supported products from independent learning and to examine whether favorable motivational responses persist beyond initial exposure. This distinction is especially relevant when students can produce polished written work without necessarily understanding its content. In physical education, evidence about engagement should therefore concern students' participation and reasoning in their courses, not simply the availability of generated explanations or assignment text (Deng et al., 2025).

Access and Responsible Use

Knowing how to operate an AI application is only one part of competent use. An exploratory review conceptualizes AI literacy through understanding, application, evaluation, and ethical awareness. For physical education students, these considerations include recognizing that an explanation may be inaccurate, checking a technical recommendation, and understanding the implications of supplying identifiable information. The proposed

instrument will record AI training and tool types as contextual information. It will not treat frequency of use as a validated measure of AI literacy (Ng et al., 2021).

UNESCO's guidance places human agency, privacy, equity, and educational appropriateness at the center of generative AI integration. These considerations have practical relevance where students might share performance recordings, personal information, or course materials with external services. The proposed study will collect survey responses without requiring students to upload such material. Questions about privacy and the availability of guidance will examine reported concerns, while responsibility for evaluating any educational application will remain with the institution and its teaching staff (Miao & Holmes, 2023).

Research Gap and Conceptual Framework

A meta systematic review of AI in higher education calls for stronger contextual, ethical, and methodological attention. The proposed study responds at a defined scale: a survey of 223 students in participating physical education programmes within Punjab. It does not assume that research is absent from Pakistan. Its contribution will be to examine three outcomes using a common recall period and explicit measures of use, while documenting access and acknowledging self-report limitations (Bond et al., 2024).

The conceptual framework positions educational AI use as the main predictor and learning motivation, self-reported sports skill competence, and academic engagement as distinct outcomes. These are hypothesized associations. Motivation may plausibly influence subsequent practice and engagement, but mediation will not be tested because the cross-sectional design cannot establish temporal order. Academic and sports-related AI use will also be examined separately in exploratory analyses to avoid hiding different patterns within one combined index.

Table 1

Conceptual alignment of the proposed variables

Predictor	Outcome	Interpretation
Educational AI use	Learning motivation	Association with interest, curiosity, and value in learning
Educational AI use	Self-reported sports skill competence	Association with perceived current skill competence
Educational AI use	Academic engagement	Association with behavioral, cognitive, and emotional involvement

Note. The framework specifies associations. It does not represent established causal pathways.

Research Methodology

Research Design

The study will employ a quantitative cross-sectional survey design. All main variables will be assessed during one data collection period, using the preceding four weeks as the common reference period where applicable. This design follows the survey approach of the model article while adapting the population and constructs to physical education. It is suitable for describing reported practices and estimating relationships. It cannot demonstrate that AI caused an improvement or that one variable preceded another. Accordingly, the title's reference to enhancement identifies the educational potential under investigation, while the empirical interpretation will remain associational.

Population and Setting

The target population will comprise adult undergraduate students enrolled in physical education or closely related sports sciences programmes at recognised higher education institutions within Punjab, Pakistan. Eligibility will require current enrolment and participation in physical education coursework during the reference period. Both AI users and non-users will be eligible. Students from institutions outside Punjab, including institutions in Islamabad Capital Territory, will not be included. Postgraduate students and staff will fall outside the proposed population. Conclusions will be bounded by the participating institutions and the recruitment achieved.

Sample and Sampling Procedure

The main survey will target 223 usable student responses. Institutions will first be selected purposively to cover northern, central, and southern Punjab, with a proposed public and private institution in each region. The regional grouping and eligible institutions will be documented before recruitment. Within each selected institution, current enrolment lists will provide the sampling frame. Students will be randomly selected within year-of-study strata, with allocations based on the institution's eligible enrolment. Because institutional selection is purposive, the complete design will not be described as a province-wide probability sample.

Table 2 specifies the proposed allocation. These figures are recruitment targets, not observed demographics. The simulated demonstration deliberately uses the same allocations. Within each institution, a randomly ordered reserve list will support further invitations when initially selected students decline or do not respond. Recruitment outcomes will be recorded for all invitations. Unplanned replacement with readily available classmates will be avoided. If a proposed institution cannot participate, a replacement from the same region and sector will be selected and documented before student recruitment begins there.

Table 2

Proposed allocation of the main sample within Punjab

Punjab region	Public institution target	Private institution target	Regional target
Northern Punjab	38	37	75
Central Punjab	37	37	74
Southern Punjab	37	37	74
Total	112	111	223

Note. Equal regional coverage is a design choice rather than proportional representation of provincial enrolment. Actual recruitment will be reported separately.

Sample Size Rationale

The main sample size of 223 is a fixed planning requirement. It will not be presented as a number derived from an unknown population total or an unperformed power analysis. An approximate sensitivity calculation using Fisher's correlation transformation indicates that 223 independent complete observations provide about 80% power for an absolute correlation of .19 at a two-sided alpha of .05. Using .05/3 as a conservative threshold for three tests gives an approximate detectable correlation of .22. These are planning calculations, not findings. Missing data and dependence within institutions may reduce precision. Explicitly

distinguishing a fixed sample requirement from its statistical sensitivity follows guidance on transparent sample size justification (Lakens, 2022).

Instrument Development

A structured questionnaire will include a background section and 36 substantive items. Six items will measure educational AI use; six will assess learning motivation; six will assess self-reported sports skill competence; nine will assess academic engagement; three will describe technological access; and six will describe barriers. Appendix A provides the proposed wording and response formats. The items are newly drafted for this study. Their inclusion does not imply established validity or reliability, and no coefficients will be assigned before data are collected.

The questionnaire will define AI by function. Examples will include conversational systems that generate explanations and verified AI-enabled systems that analyse movement or adapt practice recommendations. Ordinary video replay, a basic stopwatch, a calculator, and an application that only displays stored information will not automatically count as AI. Students will record the tools they actually used, their main purposes, and whether the tool's AI function is known. Uncertain classifications will be retained for descriptive reporting and examined separately in sensitivity analyses.

Table 3

Proposed measurement and scoring framework

Section	Items	Response range	Planned score
Educational AI use	AI1 to AI6	0 to 4	Mean frequency index; academic and sports indices also reported
Learning motivation	LM1 to LM6	1 to 5	Mean of six items, subject to measurement evaluation
Sports skill competence	SS1 to SS6	1 to 5	Mean of six self-report items
Academic engagement	AE1 to AE9	0 to 4	Three domain means; overall mean if supported
Technological access	AC1 to AC3	1 to 5	Item summaries and a prespecified access index
Barriers	BR1 to BR6	1 to 5	Separate item summaries

Note. AI use and access are descriptive indices of different activities or resources. A single internal consistency coefficient will not be required for these indices. Barrier items will not be combined automatically.

Operational Definitions

Educational AI use will mean the reported frequency of specified AI-supported academic and sports learning activities during the preceding four weeks. The primary index will average the six coded responses. Academic use will average AI1 to AI3; sports-related use will average AI4 to AI6. These indices represent reported breadth and frequency categories, not exact time spent using AI or the quality of its output.

Learning motivation will mean students' reported interest, curiosity, and perceived value in learning physical education. Sports skills will be operationalized as self-reported competence in current practical skills, including technique, coordination, control, and consistency. This measure will not establish observed motor performance or improvement

from a baseline. Academic engagement will concern involvement in theoretical and practical course learning through behavioral, cognitive, and emotional indicators. Course grades, physical fitness, and competition success will not be treated as equivalent measures of these outcomes.

Validity of the Research Instrument

Experts in physical education, educational technology, and measurement will review construct coverage, clarity, relevance, and the distinction between AI exposure and the outcomes. Cognitive interviews with students will examine how respondents understand terms such as automated feedback and sports competence. The questionnaire will then be piloted with a small separate group of physical education students in Punjab who will not enter the main sample of 223. If an Urdu version is needed, translation, independent checking, and cognitive review will precede administration. The version completed by each respondent will be recorded.

In the main data, item distributions and preliminary dimensionality will be examined. An exploratory factor analysis using an ordinal-appropriate correlation matrix, parallel analysis, and oblique rotation will assess whether the motivation, competence, and engagement items distinguish the intended constructs. This will provide preliminary evidence rather than independent validation. Item removal or scoring changes will be justified by construct content and documented transparently. No item will be removed solely to create a favourable association or a preferred coefficient (Flake & Fried, 2020).

Reliability of the Research Instrument

Cronbach's alpha and, where an appropriate measurement model permits, McDonald's omega will be estimated for the reflective outcome scales and engagement domains. Confidence intervals and the number of valid responses will accompany the coefficients. A value around .70 may provide a preliminary point of reference, but it will not be treated as proof of validity or a reason to disregard item content. An overall alpha combining exposure, outcomes, access, and barriers will not be calculated because those sections measure different constructs. Reliability estimates will be reported as obtained (McNeish, 2018).

Data Collection Procedure

Institutional permission and ethics approval will be obtained before recruitment. Selected students will receive a participant information statement explaining the study, eligibility, voluntary participation, confidentiality, and the right to skip questions. The survey will be offered in an accessible online or paper format using equivalent wording. A non-identifying invitation code will help prevent duplicate submissions without placing names or student registration numbers in the analysis dataset. Students will be encouraged to answer independently, and teaching staff will not observe individual responses.

Data collection will take place during a defined teaching period, and the final article will report its actual dates. The invitation and reminder schedule will be consistent across institutions. The recruitment record will distinguish eligible students invited, students consenting, questionnaires returned, exclusions, and records analysed. The target of 223 will refer to usable main survey records, while valid sample sizes for individual analyses will depend on completeness. The study will not report a response rate until its numerator and denominator are known.

Ethical Considerations

Participation will have no effect on grades, team selection, attendance credit, or access to teaching. Consent will be obtained before the survey begins. No training intervention, performance recording, or upload of personal information to an AI platform will be required. Identifiable recruitment records will be stored separately from survey responses, with access restricted to authorized researchers. Small demographic groups will be reported in ways that reduce identification risk. The institution's retention requirements and the limits on withdrawal after anonymization will be explained in the participant information sheet.

Data Analysis Procedure

Data will first be checked for eligibility, duplicates, out-of-range values, missingness, and inconsistencies. A response of zero to an AI-use item will mean no reported use and will not be recoded as missing. Responses such as not applicable or unable to judge will be coded as missing rather than as neutral. Outcome scores will be calculated when at least five of six motivation or competence items are available. Each engagement domain will require all three items, and an overall engagement score will require at least eight of nine items and representation of every domain. All six exposure items and all three access items will be required for their primary indices.

Frequencies and percentages will describe categorical characteristics. Means, standard deviations, medians, interquartile ranges, and observed ranges will summaries indices and outcomes as appropriate. Item response distributions will be retained so that a mean does not conceal non-use or polarized responses. No arbitrary low, moderate, and high categories will be imposed on the scales without an external justification. Descriptive tables will report the valid denominator for each variable.

The three primary analyses will estimate Pearson correlations between the educational AI-use index and each outcome, provided the proposed composite scores and their distributions support this approach. Scatterplots, influential observations, and linearity will be assessed; Spearman correlations will provide sensitivity estimates. Holm's procedure will control the family-wise error rate at .05 across the three primary tests. Effect sizes and 95% confidence intervals will be reported alongside raw and adjusted p values. Confidence intervals will be identified as individual intervals rather than simultaneous intervals.

Exploratory regressions will examine each outcome in relation to AI use while adjusting for year of study, weekly sports practice hours, access, and institutional fixed effects. Academic and sports-related AI indices will also be examined separately. These models will estimate adjusted associations, not causal effects. Residual behaviour, collinearity, and influential cases will be evaluated. Institution fixed effects will address measured site differences but will not by themselves eliminate within-site dependence. Given the proposed small number of institutions, inferential uncertainty from clustering will be acknowledged, and leave-one-institution-out sensitivity analyses will assess dependence on individual sites.

Any comparisons by institutional sector, gender, or region will be exploratory and will depend on adequate group sizes. Welch procedures may be used where mean comparisons are appropriate. Sector and region will not be entered alongside a complete set of institution indicators when this creates collinearity. Missingness will be described by variable and institution. If it materially affects inference, a documented imputation or sensitivity strategy will be added with its assumptions stated. IBM SPSS Statistics or equivalent software will

support the analyses, with the actual software versions and any psychometric extensions recorded.

Procedural safeguards will include neutral wording, separate exposure and outcome sections, and the assurance that favorable opinions about AI are not expected. These measures can reduce some common method risks but cannot remove all bias from a single self-report survey. A one-factor diagnostic will not be presented as evidence that common method bias is absent (Podsakoff et al., 2003).

Statistical Demonstration Using Simulated Data

All numerical results in this section were calculated from 223 synthetic records created for illustration. No students were surveyed, no expert panel was convened, and no institutional data were used. The six institution identifiers are fictional codes. The results illustrate statistical reporting and cannot be presented as findings about physical education students in Punjab. The proposed real study and questionnaire remain subject to review and data collection.

Simulation and Analysis Method

A single dataset was generated using NumPy random seed 20261123. The allocation was fixed at 75 northern, 74 central, and 74 southern Punjab records, with 112 public-sector and 111 private-sector records. Gender, age, locality, training, and item responses were simulated. Positive relationships between AI-use propensity and the learning factors were deliberately included in the generating model. Consequently, a positive estimate is a consequence of the simulation assumptions rather than evidence that AI improves learning.

The 36 item responses follow the proposed questionnaire ranges. There are no missing values in this demonstration, and every displayed analysis uses N = 223 unless a subgroup size is shown. Scale means follow the prespecified item groupings. Alpha confidence intervals use 2,000 record-level percentile bootstrap samples. Exploratory principal axis factoring uses Pearson item correlations with ProMax rotation, complemented by 500 column-permutation parallel-analysis samples. This is an illustrative approximation for ordered responses; ordinal-appropriate analysis remains preferable for field validation.

Pearson correlations use Fisher-transformed confidence intervals and two-sided tests. Spearman rank correlations provide a sensitivity comparison. Three primary tests are adjusted with Holm's procedure. Regression models use institutional indicators and HC3 heteroscedasticity-robust standard errors, with asymptotic normal Wald tests and 95% confidence intervals. Sector comparisons use Welch t tests; regional comparisons use Welch one-way ANOVA. Each family of three group tests receives its own Holm adjustment. These calculations were performed using Python, NumPy, and pandas, not SPSS. Institution effects do not make the uncertainty estimates cluster-robust.

Demographic Characteristics

Table 4

Simulated demographic characteristics with frequencies and percentages

Variable	Category	Frequency	Percentage
Gender	Male	140	62.8
	Female	83	37.2
Age in years	18 to 20	109	48.9

Variable	Category	Frequency	Percentage
	21 to 23	104	46.6
	24 and above	10	4.5
Year of study	1	54	24.2
	2	60	26.9
	3	57	25.6
	4	52	23.3
Institutional sector	Public	112	50.2
	Private	111	49.8
Punjab region	Northern	75	33.6
	Central	74	33.2
	Southern	74	33.2
Home locality	Urban	118	52.9
	Semi-urban	50	22.4
	Rural	55	24.7
Prior AI training	Yes	78	35.0
	No	145	65.0
Educational AI use	Any use	172	77.1
	No use	51	22.9

Note. Simulated data only. Each demographic variable totals 223 records. Percentages use 223 as the denominator; rounding can produce a total of 99.9% or 100.1%. Region denotes the fictional institution location, while home locality is a separate characteristic.

The synthetic dataset contains 140 male records (62.8%) and 83 female records (37.2%). Public and private allocations are almost equal by design, while 51 records (22.9%) show no reported AI use. These figures describe the generated dataset and do not estimate the demographics or AI-use prevalence of actual Punjab students.

Descriptive Statistics

Table 5

Simulated descriptive statistics for the study variables

Variable	N	Mean	SD	Minimum	Maximum
Educational AI use	223	1.521	1.067	0.000	4.000
Academic AI use	223	1.686	1.204	0.000	4.000
Sports AI use	223	1.356	1.059	0.000	4.000
Learning motivation	223	3.231	0.934	1.167	5.000
Sports skill competence	223	3.238	0.966	1.000	5.000
Academic engagement	223	2.225	0.710	0.444	4.000
Behavioral engagement	223	2.218	1.024	0.000	4.000
Cognitive engagement	223	2.208	1.005	0.000	4.000

Variable	N	Mean	SD	Minimum	Maximum
Emotional engagement	223	2.250	1.072	0.000	4.000
Access index	223	3.254	1.001	1.000	5.000

Note. Simulated data only. AI-use and engagement responses range from 0 to 4; motivation, sports competence, and access responses range from 1 to 5. Differences in scale ranges preclude direct comparison of the raw means across these constructs.

Reliability Analysis

Table 6

Simulated internal consistency and corrected item total correlations

Scale	Items	Alpha	95% CI for alpha	Omega	Item total range
Learning motivation	6	0.846	[0.809, 0.875]	0.847	[0.572, 0.664]
Sports skill competence	6	0.869	[0.841, 0.891]	0.870	[0.633, 0.714]
Behavioral engagement	3	0.755	[0.690, 0.808]	0.758	[0.559, 0.623]
Cognitive engagement	3	0.680	[0.597, 0.746]	0.688	[0.456, 0.555]
Emotional engagement	3	0.779	[0.723, 0.824]	0.780	[0.592, 0.631]
Academic engagement	9	0.722	[0.662, 0.768]	Not estimated	[0.344, 0.466]

Note. Simulated data only, N = 223. Omega is a standardized one-factor principal-axis estimate for each unidimensional block. It is not estimated for the nine-item multidimensional engagement composite. Alpha uses raw item covariances; item total values are correlations with the sum of the remaining items. AI-use, access, and distinct barrier items are not forced into reflective reliability models.

Motivation and sports competence have simulated alpha values of .846 and .869. The cognitive engagement domain has alpha = .680 and omega = .688, so the demonstration does not support describing all domains as meeting a .70 convention. Its wording and construct coverage would need examination in a real pilot; the generated items were not altered to raise this coefficient.

Validity Assessment

Table 7

Simulated factorability checks and status of content validity

Assessment	Result or status	Interpretation
Content and face validity	Not assessed	Requires actual expert review and student cognitive interviews
I-CVI and S-CVI	Not available	No expert ratings exist; N = 223 cannot supply these ratings
KMO overall	0.821	Item correlations are suitable for this illustrative factor analysis
Bartlett test	Chi squared = 1647.357; df = 210; $p < .001$	Generated item correlation matrix differs from an identity matrix

Assessment	Result or status	Interpretation
Parallel analysis	5 factors; 500 permutations	Five factors exceed the corresponding 95th percentile null eigenvalues
Criterion validity	Not assessed	No independent achievement or observed sports performance criterion

Note. Simulated data only. Statistical factorability does not establish content validity, criterion validity, or validity for real students. The analysis covers the 21 motivation, sports competence, and engagement items, excluding formative indices and separate barriers.

Table 8

Simulated exploratory loading ranges and convergent validity diagnostics

Construct	Pattern loadings	AVE	CR	AVE reference
Learning motivation	[0.612, 0.757]	0.480	0.847	Below .50
Sports skill competence	[0.675, 0.776]	0.527	0.870	At least .50
Behavioral engagement	[0.651, 0.805]	0.512	0.758	At least .50
Cognitive engagement	[0.568, 0.792]	0.429	0.688	Below .50
Emotional engagement	[0.693, 0.793]	0.541	0.780	At least .50

Note. Simulated data only. Pattern loading ranges come from the five-factor oblique model. AVE and CR are diagnostic approximations from separate standardized one-factor blocks, assuming uncorrelated residuals; they are not confirmatory-model estimates. CR equals the reported omega under that specification. A conventional AVE reference is .50, which should be interpreted with the measurement model and substantive content (Fornell & Larcker, 1981).

The simulated AVE values for learning motivation (.480) and cognitive engagement (.429) fall below .50. Thus, the table shows mixed convergent diagnostics rather than uniformly satisfactory validity. The real instrument requires review and independent evaluation even where the simulated factor loadings or CR appear favorable.

Table 9

Simulated heterotrait monotrait ratios for the five reflective constructs

Construct pair	HTMT
Learning motivation and Sports skill competence	0.119
Learning motivation and Behavioral engagement	0.147
Learning motivation and Cognitive engagement	0.245
Learning motivation and Emotional engagement	0.433
Sports skill competence and Behavioral engagement	0.130
Sports skill competence and Cognitive engagement	0.213
Sports skill competence and Emotional engagement	0.150
Behavioral engagement and Cognitive engagement	0.213
Behavioral engagement and Emotional engagement	0.248
Cognitive engagement and Emotional engagement	0.378

Note. Simulated data only. HTMT uses average absolute inter-construct item correlations divided by the geometric mean of within-construct item correlations. The observed ratios are below .85 in this generated example. This is an exploratory diagnostic, without an HTMT bootstrap interval, and is not proof of validity in the target population (Henseler et al., 2015).

Correlations and Hypothesis Tests

Table 10

Simulated primary correlations between educational AI use and each outcome

Outcome	Pearson r	95% CI	Raw p	Holm p	Spearman rho
Learning motivation	0.385	[0.267, 0.491]	< .001	< .001	0.348
Sports skill competence	0.270	[0.144, 0.388]	< .001	< .001	0.253
Academic engagement	0.513	[0.409, 0.604]	< .001	< .001	0.520

Note. Simulated data only, N = 223. Pearson intervals are individual 95% intervals, not simultaneous intervals. Holm correction covers the three Pearson tests. Spearman p values are approximate rank-based t tests and are all below .001 after a separate Holm correction in this demonstration.

The simulated correlations are positive for motivation (r = .385), sports competence (r = .270), and overall engagement (r = .513). All three primary tests remain below .001 after Holm adjustment, and the rank correlations show the same direction. These results demonstrate how H1 to H3 would be reported if observed; they do not provide empirical support for the hypotheses because the data were generated with positive relationships.

Overall engagement is used here as an equal-weight descriptive composite of three domains. A separate, validated higher-order engagement model has not been established. Its relationship with AI use should therefore be interpreted as a composite-index association in this demonstration.

Adjusted Regression Analysis

Table 11

Simulated regression estimates for educational AI use adjusted for covariates

Outcome	B	95% CI for B	Beta	p	Adjusted R squared
Learning motivation	0.312	[0.206, 0.419]	0.357	< .001	0.175
Sports skill competence	0.211	[0.097, 0.325]	0.234	< .001	0.168
Academic engagement	0.348	[0.275, 0.420]	0.523	< .001	0.256

Note. Simulated data only. Each model uses 223 records, 9 predictor degrees of freedom, and 213 residual degrees of freedom. Covariates are year of study, weekly practice hours, access, and five institution indicators. Confidence intervals and tests use HC3 robust standard errors with normal-reference Wald inference; they do not adjust for clustering. Full model coefficients appear in Appendix B.

The simulated AI-use coefficients remain positive after adjustment: B = .312 for motivation, .211 for sports competence, and .348 for engagement. Adjusted R squared values are .175, .168, and .256 for the complete models. These are model associations in generated data, with no causal or population interpretation.

Welch Independent Samples Tests

Table 12

Simulated public and private sector comparisons using Welch t tests

Outcome	Public mean (SD)	Private mean (SD)	t and df	Raw p	Holm p
Learning motivation	3.266 (0.924)	3.195 (0.948)	0.568 (220.73)	0.571	1.000
Sports skill competence	3.205 (0.942)	3.272 (0.993)	-0.512 (220.17)	0.609	1.000
Academic engagement	2.183 (0.764)	2.268 (0.651)	-0.902 (216.18)	0.368	1.000

Note. Simulated data only. Public n = 112 and private n = 111. Tests are two-sided and use unequal-variance degrees of freedom. Holm correction covers three sector tests. Sector is represented by fictional institutions and is not a randomized treatment.

Table 13

Simulated sector means differences with confidence intervals and effect sizes

Outcome	Public minus private	95% CI	Hedges g
Learning motivation	0.071	[-0.176, 0.318]	0.076
Sports skill competence	-0.066	[-0.322, 0.189]	-0.068
Academic engagement	-0.086	[-0.273, 0.102]	-0.120

Note. Simulated data only. Hedges g uses the pooled within-group standard deviation and a small-sample correction; confidence intervals shown are Welch intervals for the raw mean difference, not for g.

None of the three simulated sector comparisons is statistically significant. Each raw mean-difference interval includes zero, and the absolute Hedges g values are small. This illustrates reporting of uncertain group differences without treating a non-significant test as proof that the groups are equivalent.

Welch One Way Analysis of Variance

Table 14

Simulated outcome means by Punjab region

Outcome	Region	n	Mean	SD
Learning motivation	Northern	75	3.236	0.860
Learning motivation	Central	74	3.023	1.022
Learning motivation	Southern	74	3.435	0.879
Sports skill competence	Northern	75	3.158	0.976
Sports skill competence	Central	74	3.167	0.993
Sports skill competence	Southern	74	3.392	0.923
Academic engagement	Northern	75	2.237	0.668
Academic engagement	Central	74	2.161	0.717
Academic engagement	Southern	74	2.278	0.748

Note. Simulated data only. Regional labels refer to the planned fictional institution grouping, not to estimates for all institutions in a region.

Table 15

Simulated Welch one way ANOVA across the three Punjab regions

Outcome	Welch F	df1	df2	Raw p	Holm p
Learning motivation	3.459	2	145.77	0.034	0.102
Sports skill competence	1.461	2	146.53	0.235	0.471
Academic engagement	0.492	2	146.20	0.612	0.612

Note. Simulated data only. Group sizes are 75, 74, and 74. Holm correction covers the three regional outcome tests. A post-hoc family of pairwise Welch comparisons would be examined only after an adjusted omnibus test below .05.

Learning motivation has an unadjusted regional p value of .034, which increases to .102 after Holm adjustment. None of the three regional tests meets the adjusted .05 criterion. Consequently, no regional post-hoc comparisons are interpreted in this demonstration.

Diagnostics and Interpretation Limits

The maximum variance inflation factor across the fitted models is 1.723. Leaving out one fictional institution at a time gives AI-use B ranges of 0.283 to 0.341 for learning motivation; 0.182 to 0.244 for sports skill competence; 0.329 to 0.370 for academic engagement. These are sensitivity diagnostics on the simulated design. They do not address unmeasured confounding or supply cluster-level replication.

The simulation illustrates a complete workflow from item-level data to demographic, reliability, validity-related, and inferential tables. It does not represent an empirical study, establish the instrument's validity, or support educational policy claims. Real data collection must replace this demonstration before the article is presented as participant-based research.

Discussion Framework

The following discussion concerns the proposed empirical study. The simulated results above do not supply evidence for substantive conclusions about students.

The discussion will interpret each outcome separately and compare the estimates with research addressing a similar AI function and educational task. An association involving academic chatbot use will not be treated as equivalent to an intervention involving automated movement analysis. The discussion will also distinguish the proposed study's cross-sectional evidence from experimental evidence. These distinctions will prevent apparent agreement across studies from obscuring differences in what was measured.

If greater AI use is positively associated with motivation, the interpretation will consider whether access to explanations and actionable feedback is consistent with interest and perceived value. It will also consider reverse direction: students who are already motivated may seek additional learning resources more often. A weak or uncertain association could indicate that use frequency is a poor proxy for instructional quality, that activities differ in relevance, or that estimates lack precision. The theoretical account will be used to explain possibilities rather than identify an unmeasured psychological process as an established mechanism.

Any relationship with sports competence will require particular caution. Students who train frequently or already feel competent may use performance technologies more often.

Conversely, students experiencing difficulty may seek more assistance and therefore report higher AI use alongside lower competence. A positive association will concern perceived current competence and cannot establish a gain in motor performance. Future research could address this limitation through a defined instructional unit, baseline and follow-up assessment, and a delayed test without AI support.

Engagement findings will be examined at the domain level as well as through any supported overall score. AI use might be related to thoughtful comparison of explanations while showing little relationship with emotional connection or class participation. Such a pattern would have a different practical implication from a consistent relationship across all domains. Apparent engagement may also reflect task completion assisted by AI without independent understanding. Subsequent research should therefore include learning tasks that students complete without generated answers.

The access and barrier results will be discussed as experiences of the sampled students. For example, a high prevalence of reported connectivity difficulty would support investigating access arrangements in participating programmes; it would not establish a province-wide prevalence. Recommendations will be proportionate to the achieved sample, uncertainty, and feasibility. Any difference between unadjusted and adjusted estimates will be considered as evidence that contextual factors matter, while acknowledging that statistical adjustment cannot remove all confounding.

Limitations and Future Research

The cross-sectional design will limit causal and temporal interpretation. Self-report may introduce recall error, social desirability, and shared method bias, while sports competence will remain distinct from objectively measured skill. Purposive institutional selection, voluntary response, and the fixed sample of 223 will restrict generalization beyond participating programmes. Regional balance will not establish proportional provincial representation. The small number of institutions will limit precise estimation of institutional effects and robust adjustment for dependence. Newly developed items will require further validation, and different AI functions may be incompletely represented by a single exposure index. Future studies should use larger institutional samples, independent measures of engagement, and sport-specific performance assessments. Longitudinal or randomized designs could examine baseline differences, the quality of AI feedback, retained learning, and whether access conditions influence the benefits of a clearly defined instructional intervention.

Conclusion

The proposed study will examine educational AI use in relation to learning motivation, self-reported sports skill competence, and academic engagement among 223 physical education students in Punjab, Pakistan. Its contribution will depend on careful measurement, transparent reporting, and appropriate interpretation of uncertainty. The design can provide evidence about reported practices and associations within participating institutions. Evidence that AI enhances actual sports performance or causes stronger academic engagement will require a subsequent design capable of testing change and alternative explanations. The planned survey will provide a defined starting point for that work. The accompanying statistical demonstration uses simulated data and must be replaced by an analysis of actual responses before making empirical claims.

Recommendations for Study Implementation

1. Confirm participating institutions and sampling frames within Punjab before issuing invitations.
2. Complete expert review, cognitive interviews, and pilot revisions before collecting the main 223 responses.
3. Record the AI function and educational purpose rather than classify every digital application as AI.
4. Preserve non-users in the sample and document access conditions without assuming regional or sector differences.
5. Report all reliability coefficients and hypothesis estimates as obtained, together with uncertainty and missingness.
6. Base final teaching recommendations on the analysed evidence and evaluate promising practices through subsequent intervention studies.

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