STEM Education

https://www.aimspress.com/journal/steme

STEM Education, 6(4): 659–696
DOI:10.3934/steme.2026027
Received: 09 January 2026
Revised: 20 May 2026
Accepted: 10 June 2026
Published: 02 July 2026

Research article

AI in sports-sciences education in Türkiye: A qualitative study informing the artificial intelligence sports training systems integration model (AISTSIM)

Erol Baykan[1], **Ergun Gide**[2] **and Mahmoud Elkhodr**[2,*]

[1] Faculty of Sports Sciences, Yozgat Bozok University, Yozgat, Türkiye; erol.baykan@bozok.edu.tr

[2] School of Engineering and Technology, Central Queensland University (CQU), Sydney, NSW, Australia; e.gide1@cqu.edu.au, m.elkhodr@cqu.edu.au

* **Correspondence:** Email: m.elkhodr@cqu.edu.au; ORCID: 0000-0001-9904-7551.

Academic Editor: William Guo

Abstract: This study examined the integration challenges and opportunities for artificial intelligence (AI) in sports-sciences education through the development of the artificial intelligence sports training systems integration model (AISTSIM). A qualitative case study methodology was employed, drawing on semi-structured interviews with 15 academics from Yozgat Bozok University's Faculty of Sports Sciences to investigate perceptions of AI implementation, associated challenges, and ethical considerations. Thematic analysis revealed support for AI's capacity to enhance personalized learning and evidence-based training practices, while identifying significant concerns regarding data security, faculty preparedness, infrastructure, and the need for human oversight. Inter-coder reliability was established through Cohen's kappa coefficients ranging from 0.625 to 0.867, indicating substantial to almost perfect agreement. The findings informed the AISTSIM as an empirically informed conceptual implementation framework organized around five stages: data foundation, intelligent processing, interactive applications, personalized output, and comprehensive system integration. The model incorporates human-centered decision points and ethical safeguards while addressing institutional readiness and educational platform compatibility. The study contributes a theoretically positioned framework for AI integration in sports-sciences education and identifies validation pathways for future Delphi review, pilot deployment, usability testing, and longitudinal evaluation.

Keywords: artificial intelligence, sports-sciences education, faculty perceptions, qualitative thematic analysis, human-in-the-loop oversight, AISTSIM, human-centered AI, sports pedagogy

1. Introduction

The sporting world is undergoing rapid digital transformation, particularly driven by developments in artificial intelligence (AI) [1, 2]. This transformation is revolutionizing how sports activities are analyzed and optimized across various dimensions [3, 4]. AI enables computer systems to undertake tasks traditionally requiring human intelligence, such as speech recognition, decision-making, and pattern recognition, with enhanced efficiency while supporting applications including natural language processing, video analysis, and problem-solving [5].

Traditional evaluation methods typically rely on coaches' or experts' personal experiences and intuition, whereas AI introduces scientific objectivity to this process. By analyzing and comparing large volumes of data, more comprehensive and accurate evaluation results can be achieved. Consequently, an athlete's performance transforms from an uncertain concept into a numerically measurable and comparable indicator [6].

Coaches and trainers can utilize AI-supported performance analysis to gain deeper insights into players' strengths and weaknesses, facilitating the development of specialized training programs to optimize both individual and team performance [7]. AI advances this further by enabling intelligent decision-making based on data patterns. Machine learning, a branch of AI involving algorithms that learn from data to predict outcomes or classify objects, represents a significant component of this technological advancement [8].

The rise of AI in sports science necessitates academic institutions to adapt their curricula to equip future sports professionals with essential skills. This includes providing comprehensive education in data analysis, machine learning, and the ethical implications of AI technologies [9]. Future sports scientists must be proficient in interpreting complex AI-generated data and translating these insights into practical training and improvement strategies. Additionally, students should learn data visualization techniques and the use of dynamic interfaces to present complex data in user-friendly formats. By doing so, they will be better equipped to collaborate with coaches and decision-makers, ensuring AI insights are actionable and easily interpretable [10].

The integration of AI with physical education represents an inevitable trend in the development of information technologies in education. With continuous innovation in information technologies, the education sector continues to explore how these advanced technologies can be integrated into teaching practices [11–14]. The integration of AI technology in physical education will bring numerous changes to teaching processes. Intelligent technologies assist in personalizing physical education instruction. Furthermore, the integration of AI with physical education will contribute to developing students' innovative potential [16,21]. The integration of AI with physical education, while being a necessity for digitalization in education, also represents an important step in the intelligence-based and modernized development of physical education [15].

Currently, the feasibility of integrating AI technology into physical education training systems has been demonstrated from multiple perspectives. Educational institutions and research teams worldwide are increasingly exploring and successfully implementing this new model [16]. The implementation of AI technology enables optimal allocation and sharing of educational resources through intelligent data analysis and resource management [17].

At the intersection of AI and physical education, an innovative intelligent sports training system emerges, integrating sensor technology, big data analysis, and machine learning algorithms.

This system monitors athletes' physiological data in real time, conducts movement analyses, and comprehensively evaluates their performance [5]. The system can accurately assess athletes' abilities and form conditions, providing coaches with scientific and objective data to ensure training programs are more precise and targeted. Athletes can also achieve personalized development through clear analysis of their strengths and weaknesses [15].

Within the Turkish context, available syntheses indicate a noticeable emphasis on conceptual and mapping work, with comparatively fewer classroom intervention trials reported to date [18, 19]. Addressing this gap, this research aims to develop a model proposal for integrating AI-based intelligent training systems into sports-sciences education and training systems, guided by the perspectives of academics working in sports sciences, while presenting a scenario-based strategic approach.

To this end, this paper makes the following contributions to the field of AI integration in sports-sciences education:

1. Development of a comprehensive five-stage conceptual implementation framework—the artificial intelligence sports training systems integration model (AISTSIM)—providing a systematic structure for implementing AI-based intelligent training systems in higher-education sports programs.
2. Empirical grounding through qualitative stakeholder analysis: presenting thematically analyzed perspectives from 15 sports-sciences academics with established inter-coder reliability (Cohen's kappa values ranging from 0.625 to 0.867), offering evidence-based insights into implementation challenges and opportunities.
3. Scenario-based implementation guidance: presenting an application scenario that demonstrates how the AISTSIM may be operationalized across educational platforms and technologies, thereby bridging conceptual framework development and future pilot implementation.

The remainder of this paper is structured as follows: Section 2 provides related work. Section 3 presents the research methodology, including ethical considerations, research design, participant characteristics, data collection instruments, and analysis procedures. Section 4 presents the results through demographic analysis and thematic evaluation of participant responses. Section 5 discusses the implications of the findings in relation to existing literature. Section 6 introduces the proposed AISTSIM model, positions it against existing AI-in-education frameworks, and clarifies its theoretical and epistemological status. Sections 7 and 8 provide recommendations, limitations, future validation directions, and conclusions.

2. Related work

Recent literature confirms rapid advances in applying artificial intelligence (AI) to sports-sciences education yet also reveals unresolved pedagogical and organizational challenges. Experimental evidence shows that AI-generated training plans can equal or surpass coach-designed curricula: a five-week quasi-trial with 87 undergraduates found ChatGPT-formulated calisthenics improved flexibility, cardiovascular capacity, and core endurance as effectively as human programs [20]. Complementing this, Wang and Wang proposed a motion-capture-driven simulation framework that automates lesson planning, in-session feedback, and summative evaluation, while reporting that 60% of physical-education teachers still lack basic AI literacy, underscoring training deficits [21]. On the assessment front, Bonilla et al. profiled multidimensional fitness data using unsupervised machine learning, exposing patterns that can support data-driven personalization [22]. Li et al. extended this precision with a fuzzy-logic quality-evaluation model optimized via cuckoo-search that integrates managerial, instructor, and learner perspectives but requires high computational overhead and expert tuning [23].

Organizational analyses frame these technologies within sociotechnical systems: Naughton et al. argued that human–autonomy teaming, rather than outright automation, is essential for sustainable adoption in sports-sciences units, though empirical outcome data remain scarce [9]. Specialized AI applications also flourish: a review of 27 studies showed machine-learning models, especially Random Forests and convolutional networks, outperforming traditional checklists in predicting sports injuries, yet highlighted data-governance and privacy concerns that impede deployment [24]. A broader cross-disciplinary review documented growing use of AI/ML pipelines in elite leagues for performance optimization and clinical decision support but identified persistent ethical and standardization gaps [25]. Collectively, these findings validate AI's pedagogical promise while exposing four recurrent deficits: (i) fragmented, short-term trials rather than holistic curricular integration; (ii) limited faculty preparedness and change-management planning; (iii) insufficient long-term, cross-cultural evaluation; and (iv) underdeveloped frameworks linking technological capability with ethical, organizational, and learner-centered design. The present study addresses these deficits by proposing the AISTSIM, a five-stage, scenario-based integration model grounded in academic stakeholder perspectives and tailored to institutional realities in higher-education sports programs.

3. Methodology

3.1. Ethical approval

Ethical approval for this research was obtained from the Social and Human Sciences Ethics Committee of Yozgat Bozok University, with decision number 25/147. All participants provided written informed consent, identifiers were pseudonymized (A1–A15), and raw notes were stored on encrypted drives accessible only to the research team.

3.2. Research design

This research was designed using a qualitative case study approach. Case study research constitutes an empirical investigation that examines a contemporary phenomenon in depth and within its real-life context, particularly when the boundaries between phenomenon and context are not clearly evident [26]. A single case design was adopted in this research. This design enables in-depth information acquisition within a specific context, allowing multifaceted examination of complex social phenomena [27]. The case in this research was defined as the integration process of AI-supported intelligent training systems in the sports-sciences field.

The methodological structure of the research was conducted according to descriptive qualitative research principles. Based on the qualitative data obtained in the research, a five-stage model proposal was developed that systematically explains the integration of AI-supported systems in sports-sciences education. This model was structured according to the modeling recommendations based on Yin's [26] case study methodology, taking into account the findings obtained from thematic analysis.

3.3. Participants and recruitment

The sampling frame for this research comprised 25 academics working at the Faculty of Sports Sciences at Yozgat Bozok University (YOBU) during the 2024–2025 academic year, with whom interviews were initially planned. However, during the qualitative data collection process, the data obtained became repetitive and were evaluated as not providing new conceptual contributions. Data saturation was therefore considered to have been reached, and the interview process was terminated with a final sample of 15 participants. In qualitative research literature, the data collection process is terminated when no new information is obtained. This situation is defined as saturation and indicates the point where both codes and themes are sufficiently represented. Systematic reviews demonstrate that code and meaning saturation is generally achieved between 9 and 17 interviews [28]. Bouncken et al. [29] stated that analytical levels are critical in case or participant selection in qualitative research, and that reaching saturation in case-focused research depends not only on the number of individuals but also on the level of consistency/inconsistency in data production and the decreasing contribution of information obtained from new cases.

Eligible participants were academic staff within the faculty who taught applied or theory units in sports sciences during the 2024–2025 academic year. Administrative staff and casual tutors without current teaching responsibilities were excluded. Recruitment proceeded via a faculty-wide email invitation to all eligible staff (n = 25), followed by two reminders one week apart. Fifteen academics provided written consent (no incentives offered). Based on this information, the final participant sample comprised 15 faculty members from three departments: Coaching Education (CE) - 5 participants, Sports Management (SM) - 5 participants, and Physical Education and Sports Teaching (PEST) - 5 participants. Of the participating academics, 11 were male and 4 were female, with ages ranging between 24 and 60 years. Participants' professional experience ranged from 1 to 30 years.

A single institution was selected because the study was designed as an exploratory qualitative case study rather than a cross-institutional evaluation. The bounded case enabled in-depth examination of AI readiness, perceived risks, and implementation requirements within one sports-sciences faculty sharing a common institutional infrastructure. Maximum variation sampling across institutions was therefore not adopted at this model-development stage. However, variation was sought within the case by recruiting academics across three departments, different academic ranks, different levels of professional experience, and applied/theoretical teaching responsibilities.

Examination of academic rank distribution revealed: 4 Professors, 4 Associate Professors, 4 Assistant Professors, 2 Research Assistants, and 1 Lecturer. Most participants conduct applied courses, with only a limited number of academics indicating active use of AI-supported tools. In this context, the participant sample demonstrates diversity in terms of both technological awareness and pedagogical experience.

3.4. Data collection instrument

A semi-structured interview form developed by the researcher was used as the data collection instrument. Semi-structured interviews are frequently preferred in qualitative research as they provide a flexible yet focused structure aimed at revealing participants' experiences and views in depth [30]. The semi-structured interview form and demographic information questions were developed through comprehensive literature review on AI-based intelligent training systems integration into sports sciences, with expert opinions from three academics specialising in sports sciences, educational technologies, and AI. A pilot application was conducted with three academics, and necessary corrections regarding language expression were made before finalising the form.

Demographic questions. The demographic section asked participants to report age, gender, institution and department of employment, academic title, years of experience in sports sciences, whether they taught applied courses, whether they used AI-supported digital/simulation/analysis tools in their courses, and whether their university had AI-supported infrastructure such as wearable technology or intelligent systems including cameras, facial recognition, fingerprint identification, eye recognition, and analysis panels.

Interview questions.

1. What does the concept of intelligent training systems mean to you?
2. What is your general opinion regarding the integration of AI systems into sports sciences education and training processes?
3. Have you had experience working with digital/simulation technologies in applied courses? What are the positive/negative aspects?
4. How do you evaluate the use of technologies such as wearable technologies, smartwatches, sensors, analysis screens, and AI-supported cameras during theoretical or applied courses?
5. To what extent do you consider the use of AI-based systems in guiding and accepting students to specialisation areas and job applications to be feasible and ethically appropriate?
6. What contributions do you think monitoring academic achievement, physical development, and practical skills through the same system integrated with BOYSIS (Bozok Learning Management System), OBS (Student Information System), UZEM (Distance Education Application and Training Centre), Android, and iOS would provide?
7. What risks do you think monitoring academic achievement, physical development, and practical skills through the same system integrated with BOYSIS, OBS, UZEM, Android, and iOS would carry?

3.5. Data collection and analysis

Following comprehensive literature review, expert opinions from IT academics and sports sciences academics, and pilot application, demographic information and interview questions were prepared. Prior to commencing interviews with academics, preliminary meetings were conducted to provide information about the research and ensure voluntary participation. Data collection was conducted face-to-face in academics' offices at convenient times outside their teaching hours, with each interview lasting approximately 25-30 minutes. Participants' responses to questions were recorded in writing by the researcher beneath each question on the interview form. After all interviews were completed, data were transferred to digital format. Participants' thoughts were classified by question and prepared for content analysis. All interviews, field notes, and preliminary analysis were conducted in Turkish. A bilingual coauthor (the second author) produced an English draft via an AI-assisted translation tool (Claude Sonnet 4), then manually reviewed and corrected the output for contextual accuracy and terminology alignment. A second co-author (third author) subsequently expanded the English rendering of the results and discussion for clarity and completeness, maintaining fidelity to the Turkish source. The idiomatic expressions were retained using bracketed glosses where necessary.

Translation accuracy was verified through bilingual review. The initial English rendering was checked against the Turkish source notes for semantic equivalence, disciplinary terminology, and preservation of participant meaning. A second author then reviewed the translated excerpts for conceptual consistency with the coding framework. Where idiomatic expressions did not translate directly, literal translation was avoided and meaning-preserving English phrasing was used. The AI-assisted translation was therefore treated as a drafting aid, not as an analytical or interpretive tool.

Potential power dynamics were mitigated through voluntary recruitment, written informed consent, absence of incentives, pseudonymisation, and reporting through coded identifiers rather than names. Participants were informed that participation or non-participation would not affect their institutional role. Nevertheless, because participants were recruited from one faculty and included different academic ranks, residual power dynamics cannot be fully excluded and are acknowledged as a limitation.

Content analysis was conducted on data obtained from participants' open-ended responses, with themes created through verification by experts in sports sciences, information technologies, and AI to ensure accuracy through consensus. Participants were coded as A1-A15 by the researcher, with themes and codes determined. During coding, only role/rank metadata were visible whilst age and departmental identifiers were masked to minimise expectancy bias. Codes were organised in Excel with frequency (f) and percentage (%) values systematically created and presented in tabular form. During this process, repetitive expressions were grouped without disrupting semantic integrity, preserving qualitative wholeness. During digitisation, all handwritten notes were double-entered and cross-checked by an independent coder against the original field notes to reconcile discrepancies; a concise audit trail (field-note scans, change log, and codebook versioning) was maintained to document transformations from raw notes to the analysable corpus.

Based on data obtained from interviews, themes were systematically grouped inspired by Chermack's [31] scenario planning approaches, which provide effective structuring in strategic foresight and organisational decision-making processes. A five-stage integration model (AISTSIM) was developed in light of the findings. Based on this model, a scenario-based application example was structured and linked to existing literature.

Following thematic analysis completion, model development proceeded through systematic mapping of empirical findings to design requirements. Each identified theme was examined for implementation implications through a structured analytical framework. Theme frequencies and participant emphasis guided prioritisation of model components, whilst specific participant concerns informed design constraints and safeguards. A cross-reference matrix was constructed linking themes to model stages, with implementation requirements derived from participant responses regarding benefits, risks, and conditional acceptance criteria.

Saturation was operationally determined through an interview-by-interview coding progression review rather than through a pre-specified quantitative saturation grid. Successive interview records were compared with the evolving codebook to assess whether new code categories, theme-level meanings, or implementation requirements were still emerging. Data collection was stopped when additional interviews repeated existing codes and confirmed established themes rather than producing substantively new conceptual categories. The absence of a formal prospective saturation grid is acknowledged as a methodological limitation.

Negative and disconfirming cases were actively considered during analysis. Responses expressing ethical concern, scepticism, infrastructure limitations, data-security risks, and concern about the loss of human qualities in evaluation were not treated as peripheral comments. Instead, they were coded as distinct themes and used to shape the model's safeguards, particularly the human-supervision gates, data-security layer, phased implementation logic, and institutional-readiness requirements.

3.6. Validity and reliability

An initial codebook was iteratively refined with inductive codes emerging from the pilot data. Prior to full coding, two interview records were independently double-coded to calibrate application of the codebook. Discrepancies were discussed until consensus was reached, and a stability threshold of $\kappa \geq 0.60$ was set before proceeding. To minimise expectancy bias, coder access to demographic identifiers was restricted: only role/rank was visible during coding, with age and department masked. To ensure research reliability, various strategies were implemented including: literature review, expert opinions, and pilot application in creating interview and demographic information questions; theme creation with experts in three different fields; verification of created themes with five participants; and comparison with sports sciences experts to measure inter-coder consistency (Cohen's Kappa coefficient).

Cohen's Kappa coefficient reveals the actual level of agreement by comparing observed agreement with chance agreement rates [32]. Accordingly, themes were evaluated separately by two independent coders: a professor in the Faculty of Sports Sciences and the researcher.

Cohen's Kappa coefficients were calculated manually using cross-frequency tables created in Microsoft Excel environment for each theme. These calculations utilised Excel functions such as COUNTIFS and SUMPRODUCT with the formula $\kappa = (P_o - P_e)/(1 - P_e)$, where P_o represents the rate of coders assigning the same codes (observed agreement) and P_e represents the probability of assigning the same codes by chance (expected agreement). The kappa values calculated for each theme are presented in Table 1.

Table 1. Inter-coder agreement (Cohen's Kappa values).

Thematic source table	Cohen's Kappa	Agreement Level	Landis and Koch (1977) Classification
Table 3	0.734	Substantial agreement	Substantial (0.61–0.80)
Table 4	0.733	Substantial agreement	Substantial (0.61–0.80)
Table 5	0.867	Almost perfect agreement	Almost perfect (0.81–1.00)
Table 6	0.733	Substantial agreement	Substantial (0.61–0.80)
Table 7	0.671	Substantial agreement	Substantial (0.61–0.80)
Table 8	0.751	Substantial agreement	Substantial (0.61–0.80)
Table 9	0.625	Substantial agreement	Substantial (0.61–0.80)

Cohen's Kappa calculations were performed on a binary (agreement/disagreement) basis for evaluating inter-coder agreement. Cohen's Kappa coefficient indicates consistency between two coders' classifications in categorical data. Agreement level interpretation was based on Landis and Koch's [32] classification intervals: < 0.00 = Poor agreement; 0.00–0.20 = Slight agreement; 0.21–

0.40 = Fair agreement; 0.41–0.60 = Moderate agreement; 0.61–0.80 = Substantial agreement; 0.81–1.00 = Almost perfect agreement.

4. Results

4.1. Participant demographics

A total of 15 academics from YOBU participated in this research. Participants' ages ranged from 24 to 60 years, with a mean age of 41.1 years. Professional experience ranged from 1 to 30 years, with an average professional experience of 13.5 years. Eleven participants were male and four were female. Academic rank distribution was as follows: 4 Professors, 4 Associate Professors, 4 Assistant Professors, 2 Research Assistants, and 1 Lecturer. Distribution across departments was equal: 5 participants from CE, 5 participants from SM, and 5 participants from PEST. The majority of participants (13 individuals) actively taught applied courses, with only 2 participants not involved in such courses. All participants indicated that their institution lacked AI-supported intelligent system infrastructure. To reduce re-identification risk in a single-faculty case study, participant characteristics are reported in aggregate form in Table 2 rather than as individual-level demographic profiles. Participant quotations are linked only to pseudonymised identifiers (A1–A15), which were used to preserve analytic traceability without disclosing unnecessary personal detail.

Table 2. Aggregated participant demographic characteristics.

Characteristic	Distribution or summary	Reporting approach
Sample size	15 academics	Single-faculty qualitative case study
Age	Range: 24–60 years; mean: 41.1 years	Reported in aggregate to reduce identifiability
Professional experience	Range: 1–30 years; mean: 13.5 years	Reported in aggregate to reduce identifiability
Gender	11 male; 4 female	Aggregate count only
Department	CE: 5; SM: 5; PEST: 5	Aggregate count only
Academic rank	Professor: 4; Associate Professor: 4; Assistant Professor: 4; Research Assistant: 2; Lecturer: 1	Aggregate count only
Applied-course teaching	Yes: 13; No: 2	Aggregate count only
AI-supported infrastructure availability	Yes: 0; No: 15	Aggregate count only

4.2. Thematic analysis results

This section presents the thematic analysis organised in seven subsections.

4.2.1. Perceptions of intelligent training systems

Responses to the question "What does the concept of intelligent training systems mean to you?" were evaluated across three main themes. The most frequently expressed theme was Individual

Development and Personalisation at 66.7%, where participants emphasised intelligent systems' functionality in providing individual needs-based training, performance enhancement, and person-specific development support. The second theme, Technological Competence and Adaptation at 20%, highlighted AI, robotics, and contemporary technological requirements. Third, the Educational and Structural Support theme at 13.3% indicated that intelligent systems facilitate processes for both students and academics. Category frequencies and participant codes underpinning these themes are presented in Table 3.

Table 3. Thematic distribution for perceptions of intelligent training systems (n = 15 academics; multi-code allowed).

Theme	f	%	Participant Codes
Individual development and personalisation	10	66.7	A1, A7, A10, A11, A13, A14, A15, A3, A4, A5
Technological competence and adaptation	3	20.0	A2, A6, A9
Educational and Structural Support	2	13.3	A12, A8

Representative participant statements:
Theme 1: Individual Development and Personalisation

- A5: "Personalised AI-supported programmes that assist individual development can be described as systems."
- A1: "Systems that can apply tests based on a person's physical capacity and provide training programme guidance accordingly."

Theme 2: Technological Competence and Adaptation

- A6: "AI-supported structures with thinking capabilities that shape training systems according to needs, robotic structures that can respond to today's world requirements."
- A2: "Harmonising science and technology with human physiology."

Theme 3: Educational and Structural Support

- A8: "A system that facilitates the work of relevant academics and students. Also, being technology-oriented, it supports academics in current course content analysis and methodology topics."
- A12: "Systems that facilitate our work in all areas."

4.2.2. AI systems integration into sports sciences

Content analysis of responses to "What is your general opinion regarding the integration of AI systems into sports sciences education and training processes?" revealed that the "Scientific Support and Performance Development" theme showed the highest participation at 40%, indicating that a significant portion of participants evaluate AI-supported applications in terms of strengthening scientific infrastructure and individual/institutional performance enhancement. The "Generally Positive Outlook" theme represented 26.7%, demonstrating participants' open and supportive attitude towards technological developments. The "Educational Contribution and Teaching Process Integration" theme at 20% suggests that AI is valued not only in training contexts but also in instructional settings. Finally, the "Efficiency Enhancement in Training Processes" theme at 13.3% represents participant views focusing on direct field work and training planning impacts.

The distribution of responses across the four themes is detailed in Table 4.

Table 4. Thematic distribution regarding AI systems integration into sports sciences.

Theme	f	%	Participant Codes
Scientific Support and Performance Development	6	40.0	A1, A10, A11, A5, A6, A8
Generally Positive Outlook	4	26.7	A15, A3, A4, A7
Educational Contribution and Teaching Process Integration	3	20.0	A12, A13, A14
Efficiency Enhancement in Training Processes	2	13.3	A2, A9

Representative participant statements:

Theme 1: Scientific Support and Performance Development

- A1: "With these systems, more precise data in training, nutrition, competition analysis will enable more scientific lessons and training."
- A5: "I think it will help in developing anthropometric, physiological, anatomical characteristics and injury prevention."
- A6: "AI-supported systems are advanced structures capable of in-depth analysis, rapid interaction, and developing recommendations considering multifaceted variables."

Theme 2: Generally Positive Outlook

- A3: "It will bring revolutionary innovations in training sciences in the future."
- A7: "I think it accelerates and helps the sports sciences field as in all areas."

Theme 3: Educational Contribution and Teaching Process Integration

- A12: "It is positive for students' self-monitoring. It also provides convenience for academics in their work."
- A14: "It is positive as educational materials required by our age that provide advantages to us."

Theme 4: Efficiency Enhancement in Training Processes

- A2: "It will support training science."
- A9: "It supports completion of training programmes and creating personal programmes. It reduces referee errors."

4.2.3. Digital/Simulation technology experience

All participants (100%) indicated no direct experience working with digital/simulation technologies in applied courses when asked "Have you had experience working with digital/simulation technologies in applied courses? What are the positive/negative aspects?" However, in addition to stating "No," some provided positive and negative opinions. Sixty percent of participants expressed positive attitudes towards these technologies, whilst 40% highlighted negative aspects. The prevalence of non-use alongside stated positive and negative appraisals is summarised in Table 5.

Table 5. Thematic distribution regarding digital/simulation technology use in applied courses (n = 15; multiple themes per respondent possible).

Theme	f	%	Participant Codes
No Experience	15	100.0	A1-A15
Positive Views	9	60.0	A1, A2, A3, A5, A8, A10, A12, A13, A15
Negative Views	6	40.0	A1, A5, A6, A8, A12, A13

Note: All participants reported no direct experience, but some also provided positive and/or negative appraisals of potential use. A1, A5, A8, A12, and A13 contributed to both positive and negative appraisal themes. Therefore, theme frequencies should be interpreted as coded responses relative to n = 15 rather than mutually exclusive categories.

Representative participant statements:
Theme 1: No Experience

- A1-A15: "No experience."

Theme 2: Positive Views

- A2: "No experience. Positive aspects include better student development. I don't think of any negative aspects."
- A8: "No experience. The 3D visualisation effect for appropriate courses would be significant for mental visualisation and retention. This effect will increase students' learning speed and make it more permanent."

Theme 3: Negative Views

- A8: "No experience. There may be negative health consequences of digital systems."
- A13: "No experience. The system may be insufficient for crowded student groups, requiring infrastructure and financial support. Access to these systems may be difficult."

4.2.4. Smart device usage in education

Regarding "How do you evaluate the use of technologies such as wearable technologies, smartwatches, sensors, analysis screens, and AI-supported cameras during theoretical or applied courses?", 40% of participants indicated that AI-supported systems provide concrete contributions to education-teaching processes, particularly emphasising pedagogical advantages such as technical learning permanence, visual support, and individual development tracking. Twenty percent highlighted these systems' capacity for instant feedback and error risk reduction, suggesting safety benefits in applied courses. Some participants generally evaluated technology positively, emphasising its innovative and supportive nature. Another 20% focused on AI systems' data-driven analysis capacity, indicating these technologies could contribute to objective evaluation processes. Theme-level frequencies and exemplar participant codes are provided in Table 6.

Table 6. Thematic distribution regarding smart device usage.

Theme	f	%	Participants
Educational Contribution	6	40.0	A12, A14, A2, A4, A8, A9
Risk Reduction and Safety	3	20.0	A1, A10, A5
Generally Positive Views	3	20.0	A15, A3, A6
Data-driven Evaluation	3	20.0	A11, A13, A7

Representative participant statements:

Theme 1: Educational Contribution

- A2: "I think it will support learning and teaching."
- A14: "It contributes to students' learning with visual elements."

Theme 2: Risk Reduction and Safety

- A5: "Whilst more costly in laboratory environments, these systems are more risk-free and usable."
- A10: "It contributes to personal knowledge. Its use is inevitable in today's conditions. It reduces risk."

Theme 3: Generally Positive Views

- A3: "Technology use in every sense will have positive contributions to educational and learning individuals."
- A15: "I believe such tools will be beneficial."

Theme 4: Data-driven Evaluation

- A7: "Measurements, data collection, analysis, and reflection of results to training increases evaluation success."
- A11: "These are wonderful tools. Observation may mislead people, but statistics and data don't mislead."

4.2.5. AI-based systems for student guidance

Regarding "To what extent do you consider the use of AI-based systems in guiding and accepting students to specialisation areas and job applications to be feasible and ethically appropriate?", 40% of participants indicated that AI-supported systems should only be used in job guidance processes under human supervision, making them ethically safer and more applicable. At the theme level, 33.3%

focused on AI benefits without seeing ethical problems, emphasising time and resource efficiency, while 26.7% expressed that the system could be ethically problematic due to overlooking human aspects, generating bias, and personal data risks. Because responses could contain both conditional acceptance and ethical concern, these themes are reported as coded responses rather than mutually exclusive participant groups. A breakdown of conditional acceptance, positive evaluations, and ethical concerns is shown in Table 7.

Table 7. Thematic distribution regarding AI-based systems usage (n = 15; multiple themes per respondent possible).

Theme	f	%	Participants
Conditional Applicability (Human Supervision/Hybrid Approach)	6	40.0	A2, A4, A6, A9, A12, A14
Ethics and Benefit-focused Positive Approach	5	33.3	A1, A3, A7, A10, A15
Ethical Concerns and Negative Evaluation	4	26.7	A5, A6, A8, A11

Note: A6 contributed to both conditional-applicability and ethical-concern themes. Therefore, theme frequencies should be interpreted as coded responses relative to n = 15 rather than mutually exclusive categories.

Representative participant statements:

Theme 1: Conditional Applicability (Human Supervision/Hybrid Approach)

- A2: "It should be used but kept under human control. Information accuracy should be ensured."
- A14: "Ethically, the algorithm must be transparent, unbiased, and under human supervision."

Theme 2: Ethics and Benefit-focused Positive Approach

- A1: "It would be beneficial for detecting personal skills in that branch. Consequently, it contributes to better qualified personnel selection."
- A15: "It would be ethical and very beneficial. It also saves time."

Theme 3: Ethical Concerns and Negative Evaluation

- A5: "I don't think it's correct or ethical. AI may not provide real and accurate information."
- A11: "I think it's inappropriate. There are exams and interviews for employment; AI should not influence this."

4.2.6. Integrated system monitoring benefits

Regarding "What contributions do you think monitoring academic achievement, physical development, and practical skills through the same system integrated with BOYSIS, OBS, UZEM, Android, and iOS would provide?", the most widely supported themes were holistic student development and academic process facilitation (each 40%). Views on digital adaptation and necessity perception predominantly indicated that the system has become an inevitable necessity (33.3%). The full thematic distribution and multiple-coding notes are reported in Table 8.

Table 8. Perceived contributions of integrated monitoring (n = 15; multiple themes per respondent possible).

Theme	f	%	Participants
Holistic Development and Evaluation	6	40.0	A1, A3, A9, A13, A14, A11
Academic Workload and Process Efficiency	6	40.0	A5, A6, A8, A10, A12, A14
Digital Adaptation and Necessity Perception	5	33.3	A2, A4, A7, A11, A15

Note: Some participants contributed to multiple themes (A11 and A14). Therefore, theme frequencies (f) may exceed the total participant number n=15. This is a valid and acceptable practice in qualitative data analysis under multiple theme coding [28].

Representative participant statements:

Theme 1: Holistic Development and Evaluation

- A1: "Objections, error evaluation, and proof become easier in exams. Thus, students' development becomes faster by learning from mistakes."
- A14: "It provides holistic evaluation of student development, creating personalised education plans and early intervention opportunities."

Theme 2: Academic Workload and Process Efficiency

- A5: "It facilitates our work."
- A8: "It is temporally beneficial for accessing information, assignment submission, presentations, etc. Work will progress faster."

Theme 3: Digital Adaptation and Necessity Perception

- A7: "We all know the risks these systems carry. I find them appropriate because their contributions are greater than risks."
- A11: "They should definitely be used. As a Faculty of Sports Sciences, we should use these. They will certainly contribute."

4.2.7. Integrated system monitoring risks

Regarding "What risks do you think monitoring academic achievement, physical development, and practical skills through the same system integrated with BOYSIS, OBS, UZEM, Android, and iOS would carry?", participants most emphasised data security and personal information breach possibilities at 46.7%. 33.3% of participants argued that system contributions outweigh risks, expressing risk acceptability. Infrastructure deficiencies and systematic failures were seen as technical obstacles affecting application stability (20%). AI's exclusion of human qualities and making solely data-based selections were considered risky for justice and pedagogical balance (20%). The relative salience of privacy, infrastructure, impartiality, and perceived risk acceptability is summarised in Table 9

Table 9. Perceived risks of integrated monitoring (n = 15; multiple themes per respondent possible).

Theme	f	%	Participants
Data Security and Personal Information Risk	7	46.7	A1, A3, A5, A9, A13, A15, A12
Technical/Systematic Infrastructure Problems	3	20.0	A8, A10, A1
Evaluation Impartiality and Human Factor	3	20.0	A1, A2, A12
Risk Acceptability/Insignificance	5	33.3	A4, A5, A7, A11, A14

Note: Some participants contributed to multiple themes (A1 and A5). Therefore, theme frequencies (f) may exceed the total participant number n=15. This is a valid and acceptable practice in qualitative data analysis under multiple theme coding [28].

Representative participant statements:

Theme 1: Data Security and Personal Information Risk

- A5: "There is risk regarding personal information protection. But contributions are greater."
- A13: "The risk is data falling into third-party institutions' hands... Secure systems like blockchain could be established."

Theme 2: Technical/Systematic Infrastructure Problems

- A8: "However, there may be infrastructure problems."
- A10: "Systematic problems may be experienced."

Theme 3: Evaluation Impartiality and Human Factor

- A1: "There may be problems regarding different academics' evaluations teaching the same course."
- A12: "The absence of human qualities in evaluations is a risk."

Theme 4: Risk Acceptability/Insignificance

- A4: "Risks can be overlooked because contributions are significant."
- A7: "We all know the risks these systems carry. I find them appropriate because their contributions are greater than risks."

5. Discussion

5.1. Interpretation of key findings

The finding that 66.7% of participants conceptualised intelligent training systems primarily through "Individual Development and Personalisation" demonstrates a human-centred understanding of AI applications in sports education. This perspective aligns with literature indicating that AI-supported systems excel in creating individualised training programmes and providing personalised development plans [7, 10]. The relatively lower emphasis on "Technological Competence and Adaptation" (20%) suggests that participants view technology as a means rather than an end, prioritising pedagogical outcomes over technological sophistication. This emphasis on personalisation reflects participants' understanding that sports education inherently requires individualised approaches due to varying physical capabilities, learning styles, and performance levels among students.

The predominance of "Scientific Support and Performance Development" (40%) as the primary benefit of AI integration reveals participants' emphasis on evidence-based practice in sports sciences. This finding indicates that academics perceive AI's value primarily in enhancing the scientific rigour of training and evaluation processes. The combination of "Generally Positive Outlook" (26.7%) with specific scientific benefits suggests that optimism towards AI is not merely technological enthusiasm but grounded in practical pedagogical considerations. This scientific emphasis is particularly relevant given that all participants indicated their institution currently lacks AI infrastructure, yet their positive scientific outlook suggests readiness for evidence-based AI implementation.

The finding that 100% of participants lack direct experience with digital/simulation technologies, yet 60% express positive views, reveals a critical implementation gap. This paradox suggests that whilst academics are conceptually ready for AI integration, there exists significant need for hands-on training and pilot programmes. The specific concerns raised by the 40% expressing negative views, including health impacts (A8) and infrastructure requirements (A13), provide concrete guidance for implementation planning. The positive attitude despite lack of experience suggests willingness to adopt AI technologies when appropriately supported through training and infrastructure development.

The finding that 40% of participants support AI usage only under "human supervision/hybrid approach" for student guidance represents sophisticated understanding of AI limitations and ethical considerations. This conditional acceptance, combined with 26.7% expressing ethical concerns, indicates that participants recognise both AI's potential and its risks. The emphasis on human oversight reflects professional responsibility and suggests that implementation strategies must incorporate human-AI collaboration rather than AI replacement of human judgement. Specific participant concerns about AI providing "real and accurate information" (A5) and the inappropriateness of AI influence in employment decisions (A11) highlight the need for transparency and explainable AI systems in educational contexts.

The equal emphasis on "Holistic Development and Evaluation" and "Academic Workload and Process Efficiency" (both 40%) indicates that participants view integrated AI systems as serving dual purposes: enhancing educational outcomes whilst improving operational efficiency. However, the predominant concern about "Data Security and Personal Information Risk" (46.7%) reveals that privacy considerations may be the primary barrier to implementation. The fact that 33.3% of participants consider risks "acceptable/insignificant" when balanced against benefits suggests that successful implementation requires robust security measures and transparent data handling policies.

An overview of the dominant faculty viewpoints and their mapping to implementation requirements is provided in Figure 1. It provides an overview of key qualitative findings (n = 15) and their implications for AI adoption in sports sciences education, highlighting personalisation salience (66.7%), evidence-led performance development (40%), and conditional acceptance requiring human oversight (40%), with data security emerging as the predominant risk (46.7%).

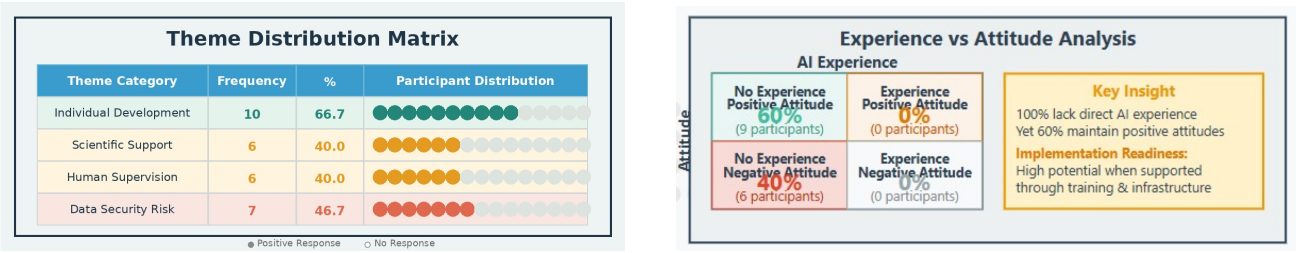

Figure 1. Key findings: Overview of key qualitative findings (n = 15) and their implications for AI adoption in sports sciences education.

5.2. Contextual significance and broader implications

The study's findings within the Turkish higher education context reveal specific implementation considerations for institutions operating with limited AI infrastructure. The absence of existing AI-supported infrastructure in the case institution, combined with positive implementation attitudes, suggests an opportunity for staged AI integration that can be designed from the outset around governance, staff development, privacy protection and pedagogical purpose. The specific integration requirements with Turkish educational platforms (BOYSIS, OBS, UZEM) mentioned by participants indicate that successful AI implementation must consider existing educational ecosystems rather than implementing standalone solutions.

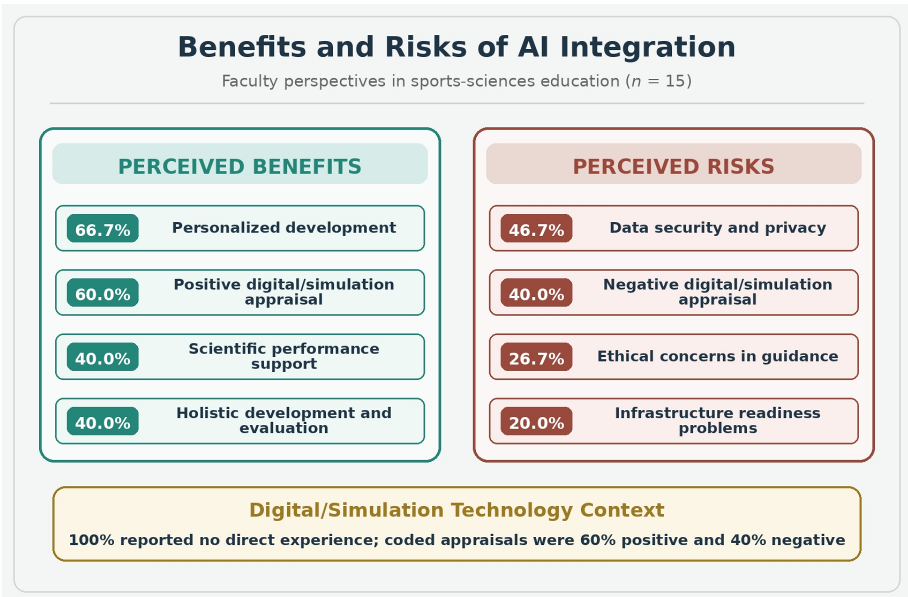

Figure 2. Perceived benefits and risks of AI integration in sports sciences education derived from thematic coding.

The finding that participants emphasise practical applications and individual development reflects the unique requirements of sports sciences education, where theoretical knowledge must translate into physical performance. The concern about maintaining "human qualities" in evaluation (A12) is particularly relevant in sports education, where motivation, teamwork, and character development are as important as measurable performance metrics. The emphasis on risk reduction and safety (20% of smart device usage responses) reflects the physical nature of sports education, where AI systems must prioritise student safety alongside learning outcomes. The perceived pedagogical and operational benefits relative to the principal risk classes are contrasted in Figure 2. The figure shows that benefits are clustered around scientific support, personalisation, and efficiency, whereas risks are concentrated on data security/privacy, infrastructure maturity, and the potential erosion of human-centred evaluation.

6. AISTSIM model proposal

The Artificial Intelligence Sports Training Systems Integration Model (AISTSIM) was developed through systematic analysis of participant perspectives, with each model component directly traceable to specific empirical findings from the thematic analysis. The model development process involved structured mapping of participant responses to implementation requirements, ensuring that design decisions reflected demonstrated stakeholder needs rather than theoretical assumptions.

The model's foundational philosophy emerged from the predominant conceptualisation of intelligent training systems through "Individual Development and Personalisation" by 66.7% of participants (Table 3). This finding fundamentally shaped the human-centred design approach, with participants A1, A5, A7, A10, A11, A13, A14, A15, A3, and A4 emphasising systems that provide individualised support rather than standardised solutions. The consistent emphasis across multiple participant responses established personalisation as the primary design requirement throughout all model stages.

The five-stage structure directly addresses the integration challenges identified through participant responses whilst incorporating the conditional acceptance requirements expressed by 40% of participants (Table 7). The systematic integration of human oversight mechanisms at each stage responds to specific concerns raised by participants A2, A4, A6, A9, A12, and A14 regarding the necessity for maintaining human authority over AI recommendations. Each stage incorporates decision points where educators retain control over system outputs, addressing participant A12's concern about preserving "human qualities in evaluations" and participant A2's requirement for systems operating "under human control."

The model's comprehensive approach to addressing implementation barriers reflects the dual emphasis identified in participant responses on both "Holistic Development and Evaluation" and "Academic Workload and Process Efficiency" (both 40%, Table 8). The integration framework acknowledges that successful AI implementation must simultaneously enhance educational outcomes whilst improving operational effectiveness, responding to the practical requirements identified by participants across all three academic departments.

6.1. Theoretical positioning and epistemological status of AISTSIM

AISTSIM differs conceptually and structurally from existing educational technology and AI-in-education frameworks in four principal ways. First, whereas TPACK and AI-TPACK primarily conceptualise the knowledge educators require to align technology, pedagogy, and content, AISTSIM translates these knowledge intersections into a staged implementation architecture for sports-sciences education [33,37]. In this sense, AISTSIM does not replace TPACK; rather, it operationalises its logic in a context where disciplinary content is inseparable from physiological data, movement analysis, practical skill development, safety, and performance feedback. Second, unlike general technology-integration models such as SAMR, which classify the extent to which technology transforms learning activity, AISTSIM specifies the institutional and pedagogical sequence through which AI-supported systems can be introduced, interpreted, governed, and sustained [34]. Third, while UNESCO's AI Competency Framework for Teachers defines teacher competencies for ethical, pedagogical and professional AI use, AISTSIM converts such competency expectations into a discipline-specific operational pathway for applied sports-sciences education [35]. Fourth, while human-centred AI and human-AI collaboration frameworks emphasise stakeholder agency, human control, trustworthiness, and ethical oversight, AISTSIM embeds human judgement throughout the full implementation cycle: data selection, AI interpretation, interactive learning design, personalised feedback, assessment moderation, and institutional integration [36].

The core theoretical contribution of AISTSIM is therefore not simply the contextual adaptation of AI-in-education principles to sports sciences. Rather, it is the integration of five dimensions that are often treated separately in the literature: learner and performance data, AI-enabled analysis, interactive pedagogical application, personalised human-interpreted outputs, and institutional governance. This integration is particularly important in sports-sciences education because AI use may involve biometric indicators, movement data, wearable technologies, simulation environments, student performance records, and high-stakes interpretations about physical development and professional readiness.

AISTSIM should be understood as an empirically informed conceptual implementation framework rather than a validated operational model. Its empirical grounding derives from qualitative stakeholder data collected from academics in one Faculty of Sports Sciences and from the systematic mapping of themes to implementation requirements. However, the present study did not pilot AISTSIM in a live educational setting, evaluate student learning outcomes, or test system usability. Accordingly, the model is best interpreted as a set of theoretically informed and empirically derived design propositions requiring further validation through expert review, pilot deployment, usability testing, and longitudinal evaluation.

Table 10. Conceptual positioning of AISTSIM against selected AI and educational technology integration frameworks.

Framework	Primary emphasis	Limitation for the present study	How AISTSIM extends it
TPACK / AI-TPACK	Alignment of technology, pedagogy and disciplinary content within teacher knowledge.	Does not provide a staged implementation pathway for AI systems involving biometric, performance, platform and governance data.	Translates technology-pedagogy-content alignment into a five-stage sports-sciences implementation sequence.
SAMR	Classifies technology use from substitution to redefinition.	Useful for describing technology transformation, but limited as an AI governance or institutional implementation model.	Moves beyond classification by specifying data, processing, interactive application, personalised output and institutional integration stages.
UNESCO AI Competency Framework for Teachers	Defines teacher competencies for ethical, pedagogical and professional AI use.	Provides competency expectations, but not a discipline-specific operational pathway for AI-supported sports-sciences education.	Converts AI competency expectations into an implementation architecture for applied sports education.
Human-centred AI / human-AI collaboration frameworks	Emphasise human agency, oversight, transparency, trust and responsible AI use.	Often remain at the level of design principles and do not specify how human judgement operates across educational stages.	Embeds human judgement across data selection, AI interpretation, learning design, feedback, assessment and governance.

The five-stage structure was selected because AI integration in sports-sciences education follows a cumulative sociotechnical sequence. The model begins with the establishment of a data foundation because AI-supported decision-making cannot occur without valid, ethically collected, and pedagogically meaningful data. It then proceeds to intelligent processing, where data are transformed into interpretable analytics. The third stage, interactive applications, translates analytics into learning experiences through simulations, dashboards, wearable technologies, or AI-supported feedback systems. The fourth stage, personalised output, converts system analysis into student-specific and educator-interpreted feedback, assessment evidence, and development plans. The fifth stage, comprehensive integration, addresses institutional embedding, platform interoperability, governance, privacy, and sustainability. The sequencing therefore reflects a progression from data readiness to analytical capability, pedagogical enactment, personalised interpretation, and institutionalisation.

Table 11. Theoretical grounding of AISTSIM stages.

AISTSIM stage	Theoretical grounding	Operational meaning
Data Foundation	Sociotechnical systems theory; AI-TPACK	Data are selected according to disciplinary relevance, pedagogical purpose, privacy requirements and institutional feasibility.
Intelligent Processing	Augmentation theory; learning analytics	AI transforms data into interpretable insights that support, rather than replace, educator judgement.
Interactive Applications	Constructivism; experiential learning	Students engage with AI-supported feedback, simulation and visualisation in applied learning contexts.
Personalised Output	Formative assessment; self-regulated learning	AI outputs are converted into individualised feedback, development plans and assessment evidence.
Comprehensive Integration	Human-centred AI; responsible innovation	AI adoption is embedded into platforms, governance, privacy, institutional workflow and sustainability planning.

AISTSIM operationalises TPACK in measurable terms by converting the abstract alignment of technology, pedagogy and content into indicators that can be observed during implementation. In the sports-sciences context, this requires measuring whether AI tools are aligned with disciplinary concepts, whether they support feedback and assessment processes, whether educators can interpret AI outputs, and whether institutional governance protects ethical and pedagogical integrity.

Table 12. Indicative measurable operationalisation of TPACK within AISTSIM.

Dimension	AISTSIM focus	Measurable indicator
Content knowledge	Match AI outputs to sport concepts: movement, injury prevention, training load and performance evaluation.	Share of AI activities mapped to learning outcomes and sport-science competencies.
Pedagogical knowledge	Use AI for feedback, scaffolding, demonstration, self-monitoring, formative assessment and reflection.	Proportion of AI tasks with feedback, reflection and educator interpretation.
Technological / AI knowledge	Build educator understanding of tools, data inputs, limitations, bias, privacy and outputs.	Pre/post AI-literacy or AI-TPACK scores; training-module completion.
Technological-content knowledge	Use sensors, wearables, analytics and simulations to represent sport-performance concepts.	Agreement between AI-derived indicators and expert judgement.
Technological-pedagogical knowledge	Improve feedback timing, learner engagement, practice quality and assessment transparency.	Feedback latency, engagement measures and perceived feedback usefulness.
Integrated AI-TPACK	Align AI tools, sport content, pedagogy, assessment, ethics and governance.	Composite readiness score covering alignment, design, AI literacy, privacy and educator oversight.

6.2. Five-stage integration framework

The resulting integration logic is codified in Figure 3, which organises AISTSIM into five staged components with embedded human-oversight gates, each systematically grounded in empirical findings. The model development was informed by established theoretical frameworks including the Technology Pedagogy and Content Knowledge (TPACK) framework for educational technology integration, constructivist learning principles emphasising active knowledge building, human-AI collaboration approaches prioritising ethical integration, and sports pedagogy focusing on individual development pathways.

Stage 1: Data Foundation establishes comprehensive data collection encompassing individual student profiling (biometric, physiological, and performance data), educational content integration (learning outcomes, skill progressions, assessment criteria), and system parameter definition (movement specifications, safety parameters, feedback protocols). This stage directly addresses the 66.7% of participants who prioritised "Individual Development and Personalisation" (Table 3), responding to participant A1's requirement for systems that "apply tests based on a person's physical capacity and provide training programme guidance accordingly" and participant A5's emphasis on "personalised AI-supported programmes that assist individual development." The objective evaluation framework addresses participant A11's assertion that "statistics and data don't mislead" whilst incorporating the infrastructure requirements that participant A13 identified as essential for successful implementation. The comprehensive data foundation responds to participant A15's conceptualisation of systems as supportive structures and participant A4's emphasis on individual needs assessment.

Stage 2: Intelligent Processing transforms data into evidence-based insights through advanced data mining, adaptive assessment mechanisms, and real-time feedback generation. This stage systematically addresses the 40% of participants who identified "Scientific Support and Performance Development" as AI's primary value (Table 4), responding to participant A6's expectation of "AI-supported structures with thinking capabilities" and "advanced structures capable of in-depth analysis, rapid interaction, and developing recommendations considering multifaceted variables." The stage incorporates participant A1's requirement for "more precise data in training, nutrition, competition analysis" to enable "more scientific lessons and training" whilst addressing participant A5's emphasis on supporting "physiological, anatomical characteristics and injury prevention." The evidence-based approach reflects participant A8's valuation of AI systems that "support academics in current course content analysis and methodology topics" and participant A10's emphasis on scientific infrastructure strengthening.

Stage 3: Interactive Applications provides safe, controlled introduction to AI-enhanced learning through VR/AR simulation technologies, cross-platform applications, and automated performance analysis. This stage systematically addresses the 100% lack of direct experience with digital/simulation technologies (Table 5) whilst building upon the 60% positive attitudes expressed by participants A1, A2, A3, A5, A8, A10, A12, A13, and A15. The design responds to participant A5's identification of AI systems as "more risk-free and usable" compared to traditional laboratory environments, whilst incorporating participant A8's emphasis on "3D visualisation effect for appropriate courses" that would provide "significant mental visualisation and retention" benefits. The safety prioritisation addresses the 40% of participants who raised negative appraisals, including participant A13's concerns about system infrastructure requirements, whilst responding to participant A2's expectation that positive aspects include "better student development" through technological enhancement.

Stage 4: Personalised Output synthesises AI analysis into accessible insights through individual reporting systems, collaborative human-AI assessment, and multi-dimensional monitoring dashboards. This stage directly responds to the equal participant emphasis on "Holistic Development and Evaluation" and "Academic Workload and Process Efficiency" (both 40%, Table 8), addressing participant A14's specific requirement for "holistic evaluation of student development, creating personalised education plans and early intervention opportunities" whilst responding to participant A1's emphasis on making "objections, error evaluation, and proof easier in exams." The collaborative assessment approach incorporates the human supervision requirements identified by 40% of participants (Table 7) whilst addressing participant A8's emphasis on temporal efficiency and participant A12's valuation of systems that provide "convenience for academics in their work."

Stage 5: Comprehensive Integration ensures seamless connection with existing educational infrastructure through educational platform harmonisation, crisis response mechanisms, and health integration features. This stage systematically addresses the 46.7% of participants who identified "Data Security and Personal Information Risk" as the primary implementation concern (Table 9), incorporating participant A13's specific recommendation for "secure systems like blockchain" whilst responding to participant familiarity with existing institutional systems (BOYSIS, OBS, UZEM). The comprehensive security framework addresses concerns raised by participants A1, A3, A5, A9, A15, and A12 regarding personal information protection, whilst the infrastructure design responds to participant A8's identification of potential "infrastructure problems" and participant A10's concern about "systematic problems." The integration approach acknowledges participant A11's position that "we should definitely use these" systems whilst incorporating the risk mitigation strategies that participants deemed essential for acceptable implementation.

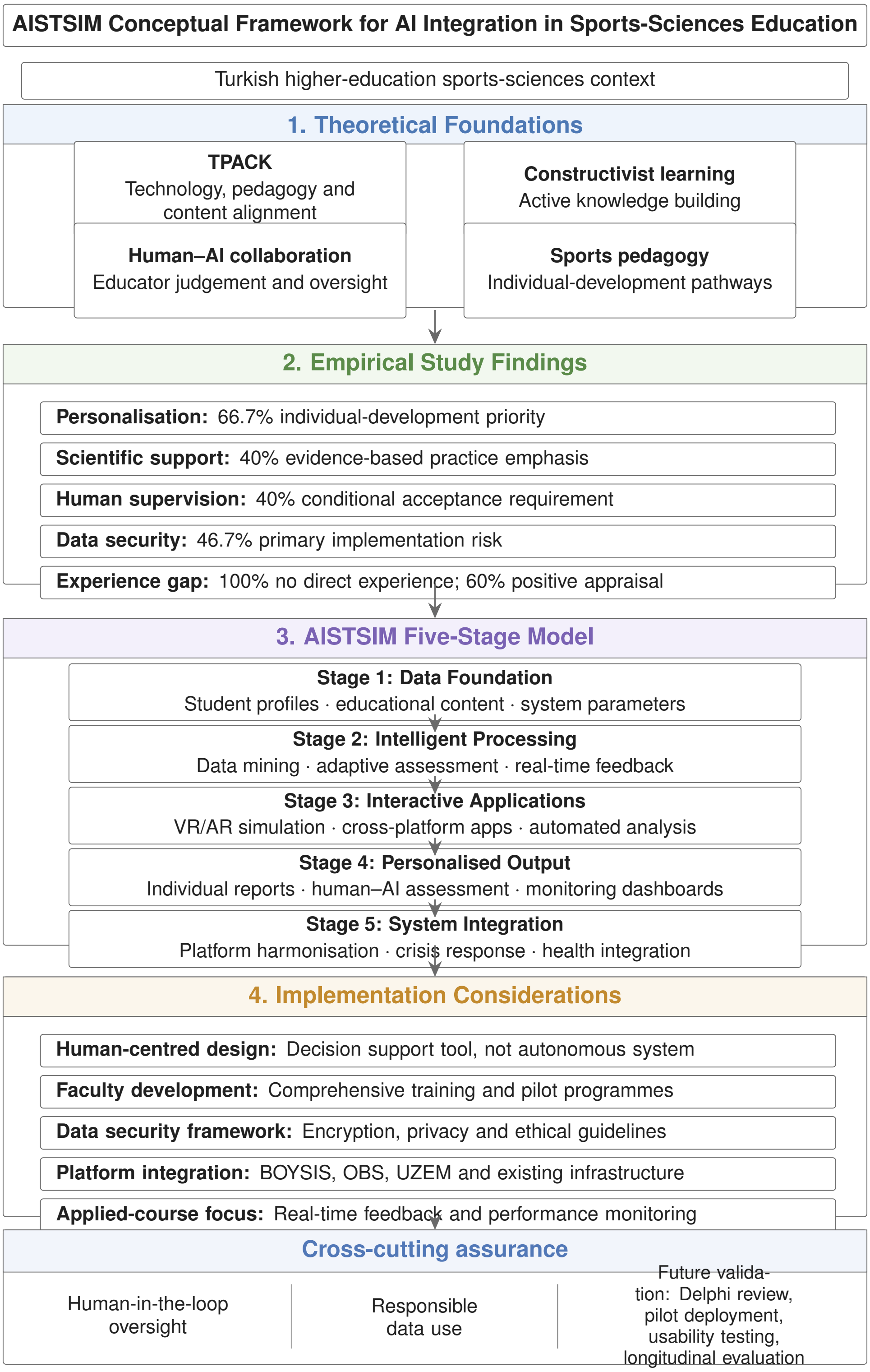

Figure 3. The AISTSIM conceptual framework showing the relationship between theoretical foundations, empirical study findings, the five-stage model, implementation considerations, and cross-cutting assurance.

The systematic relationship between empirical findings and model design is demonstrated through the theme-to-stage mapping presented in Table 13, which provides traceability between specific participant responses and corresponding model components.

Table 13. Theme-to-Model stage mapping matrix.

AISTSIM Stage	Primary Supporting Theme(s)	Theme Frequency	Key participant requirements	Design Response
Stage 1: Data Foundation	Individual Development & Personalisation	66.7% (n=10)	Personal capacity assessment (A1), Individual development support (A5)	Comprehensive student profiling, biometric integration
Stage 2: Intelligent Processing	Scientific Support & Performance Development	40% (n=6)	Scientific precision (A1), In-depth analysis (A6)	Advanced analytics, evidence-based recommendations
Stage 3: Interactive Applications	No Experience + Positive/Negative Views	100% + 60%/40%	Risk reduction (A5), Visual learning (A8), Infrastructure concern (A13)	VR/AR simulation technologies, safety protocols
Stage 4: Personalised Output	Holistic Development + Process Efficiency	40% + 40%	Comprehensive evaluation (A14), Error assessment (A1)	Individual reporting, collaborative assessment
Stage 5: System Integration	Data Security + Human Supervision	46.7% + 40%	Blockchain security (A13), Human control (A2)	Multi-layer security, human oversight gates

This mapping ensures that each model stage addresses demonstrated stakeholder needs rather than theoretical assumptions, establishing the empirical foundation for the five-stage integration framework.

6.3. Addressing participant concerns through model design

The AISTSIM model specifically incorporates design elements that address each major concern identified through the research whilst preserving the benefits that participants recognised as valuable for sports sciences education. Responding to the 46.7% of participants who identified data security as the primary implementation risk, the model incorporates multiple security layers including encryption protocols, access control mechanisms, audit trails, and the blockchain-type security measures that A13 specifically mentioned. The design ensures that privacy protection remains paramount whilst enabling the educational benefits that participants valued.

Addressing the 40% of participants who emphasised conditional applicability requiring human supervision, every stage of the model includes human decision points where educators maintain authority over AI recommendations. This design responds to concerns like those expressed by A2 about keeping systems "under human control" whilst leveraging AI capabilities to enhance rather than replace professional judgement. The model maintains transparency in AI decision-making processes, ensuring that educators understand how recommendations are generated and can override them when professional judgement indicates alternative approaches would better serve educational objectives.

Recognising the 100% lack of direct AI experience among participants, the model includes extensive faculty development programmes, pilot implementation phases, and comprehensive training approaches that build on participant readiness whilst addressing experience limitations. The phased implementation strategy begins with small-scale pilot programmes that allow faculty to gain hands-on experience before full system deployment, addressing the infrastructure and training concerns that participants like A13 identified as essential for successful adoption. This comprehensive support framework ensures successful adoption whilst respecting institutional constraints and capabilities, building confidence through demonstrated success rather than overwhelming faculty with complex technological requirements.

6.4. Model implications and future directions

The AISTSIM model represents a potential theoretical contribution to the field of AI integration in sports sciences education, addressing the gap identified in Turkish literature where studies predominantly remain at conceptual levels. The model provides systematic guidance for universities seeking to integrate AI technologies whilst maintaining pedagogical effectiveness and ethical standards that emerged as priorities through participant responses. The framework offers practical implementation pathways that balance technological advancement with human-centred educational values, ensuring that AI enhancement serves rather than replaces the fundamental elements of effective sports education.

Implementation of the model necessitates substantial institutional investment in comprehensive AI infrastructure, technical support systems, and faculty development programmes. The phased approach addresses participant concerns about infrastructure requirements whilst building on demonstrated readiness for evidence-based AI adoption revealed through the research. Success depends critically on addressing the experience gap through comprehensive training programmes whilst maintaining the human-centred values that participants consistently emphasised as central to effective sports education. The model's flexibility enables adaptation to different institutional contexts whilst preserving core design principles that emerged from participant perspectives.

The model requires extensive validation through longitudinal implementation studies, cross-institutional testing, and empirical assessment of learning outcomes to establish effectiveness and identify necessary refinements. Research priorities include examining post-implementation experiences, investigating cultural variations in AI adoption patterns, and developing comprehensive metrics for measuring AI integration effectiveness in sports education contexts. Cross-cultural validation studies would enhance the model's applicability beyond the Turkish higher education context whilst maintaining sensitivity to local educational requirements and cultural considerations.

AISTSIM has not yet been pilot-tested in an educational setting. The present study should therefore be read as a model-development and theoretical-positioning study, not as evidence of implementation effectiveness. Future work should first examine content validity, usability, feasibility, and pedagogical impact before operational claims are made.

The model's development within a single institutional context necessitates careful adaptation for different cultural and educational environments whilst preserving the human-centred design principles that emerged from participant perspectives. The emphasis on integration with Turkish educational platforms requires modification for international implementation, though the underlying framework of human-AI collaboration and ethical safeguards maintains relevance across diverse educational contexts. Future research should examine how the model's core principles adapt to different technological infrastructures and educational cultures whilst maintaining effectiveness in promoting both student learning and institutional efficiency. The AISTSIM model thus represents a systematic response to participant perspectives, incorporating their identified benefits whilst addressing their concerns through thoughtful design that maintains human-centred educational approaches enhanced rather than replaced by AI capabilities.

6.5. Optional SAGE-informed pedagogical assurance extension

As a future pedagogical extension, AISTSIM may be strengthened through a SAGE-informed assurance layer [38]. SAGE provides a useful mechanism for operationalising human judgement within AISTSIM. In particular, the SAGE emphasis on critique, justification, traceability and defence of AI-supported decisions is relevant to the personalised output and comprehensive integration stages. When an AI-supported sports-sciences system produces performance feedback, training recommendations, development profiles or risk alerts, students and educators should not treat such outputs as self-validating. Instead, they should interpret the output, assess its disciplinary plausibility, decide whether to accept, modify or reject it, and document the reasoning behind that decision. In this way, human-in-the-loop AI is extended beyond ethical supervision into an explicit pedagogical process of accountable judgement.

This assurance layer also creates a future validation pathway. For example, a pilot AISTSIM implementation could examine whether SAGE-informed tasks improve students' capacity to interpret AI-generated sport-performance data, justify training decisions, critique automated recommendations, and demonstrate accountable use of AI-supported feedback. Such a design would allow the model's pedagogical contribution to be tested through student artefacts, educator moderation records, usability measures, and comparative learning outcomes.

7. Recommendations

The AISTSIM model development and study findings provide clear guidance for implementing AI-supported systems in sports sciences education. Given that 100% of participants lacked direct digital/simulation technology experience yet 60% expressed positive views, universities should prioritise comprehensive faculty development programmes before system deployment. The positive attitude despite inexperience indicates strong readiness for adoption when supported through proper training and infrastructure development. This recommendation directly informs the phased implementation approach embedded within the AISTSIM model, ensuring that technological advancement proceeds alongside human capacity building.

Since 66.7% of participants conceptualised intelligent training systems through individual development and personalisation, AI implementation must focus on adaptive learning algorithms that respond to individual student needs rather than standardised applications. This finding fundamentally shaped the AISTSIM model's design philosophy and directly informs system design priorities for institutions seeking to adopt AI technologies. Implementation should begin with pilot programmes that demonstrate personalisation capabilities whilst building faculty confidence through observable improvements in student learning outcomes.

Responding to the 40% of participants who emphasised conditional applicability requiring human supervision, AI systems must be designed as decision-support tools rather than autonomous systems. The AISTSIM model incorporates human decision points at each stage, ensuring that educators maintain authority over AI recommendations whilst benefiting from enhanced analytical capabilities. Implementation strategies should emphasise this collaborative approach, providing training that enables faculty to effectively integrate AI insights with professional judgement rather than replacing human expertise with technological solutions.

The 46.7% of participants who identified data security as the primary implementation risk necessitate comprehensive security frameworks including encryption, multi-stage authentication, and transparent data handling policies. The specific mention of blockchain technology by participant A13 suggests incorporating advanced security solutions that address contemporary data protection requirements. Implementation must prioritise security infrastructure development alongside educational technology deployment, ensuring that privacy protection enables rather than constrains educational innovation.

7.1. Addressing implementation barriers and challenges

The study findings reveal specific barriers that require systematic attention during AI implementation in sports sciences education. Responding to concerns about infrastructure and financial support raised by participants like A13, institutions require substantial investment in comprehensive AI infrastructure, technical support systems, and scalable solutions that accommodate growing student populations. The AISTSIM model's modular design enables phased investment that spreads costs whilst building institutional capacity gradually.

The 26.7% of participants expressing ethical concerns necessitate developing comprehensive ethical guidelines specifically for AI usage in sports education contexts. These guidelines must address transparency in AI decision-making, informed consent for data collection and analysis, privacy protection throughout the system lifecycle, and algorithmic fairness that ensures equitable treatment of all students. Implementation should include ethics training for faculty and regular auditing of AI system performance to ensure continued adherence to ethical standards.

For the 20% of participants concerned about technical and systematic problems, implementation must include robust backup systems, regular maintenance protocols, and comprehensive contingency plans for system failures that ensure educational continuity. The AISTSIM model's integration with existing educational platforms provides redundancy that supports continued operation even when AI components require maintenance or experience technical difficulties.

7.2. Strategic implementation pathway

Based on the AISTSIM model and study findings, institutions should adopt a strategic implementation pathway that begins with comprehensive faculty development and pilot programme establishment. Initial implementation should focus on applied course integration, given that 86.7% of participants teach applied courses and emphasised practical applications. Real-time feedback systems and performance monitoring tools that enhance hands-on learning experiences should receive priority over theoretical applications that may not demonstrate immediate value to faculty or students. The recommended phased pathway, with capability building, governance, and infrastructure milestones, is summarised in Fig. 4.

The equal emphasis that participants placed on holistic development evaluation and process efficiency (both 40%) indicates that AI systems should integrate with existing educational platforms rather than operating as standalone solutions. Implementation should ensure compatibility with institutional systems like BOYSIS, OBS, and UZEM whilst providing enhanced analytical capabilities that serve both pedagogical and operational needs. This integration approach addresses the practical requirements identified by participants whilst building on existing technological infrastructure and user familiarity.

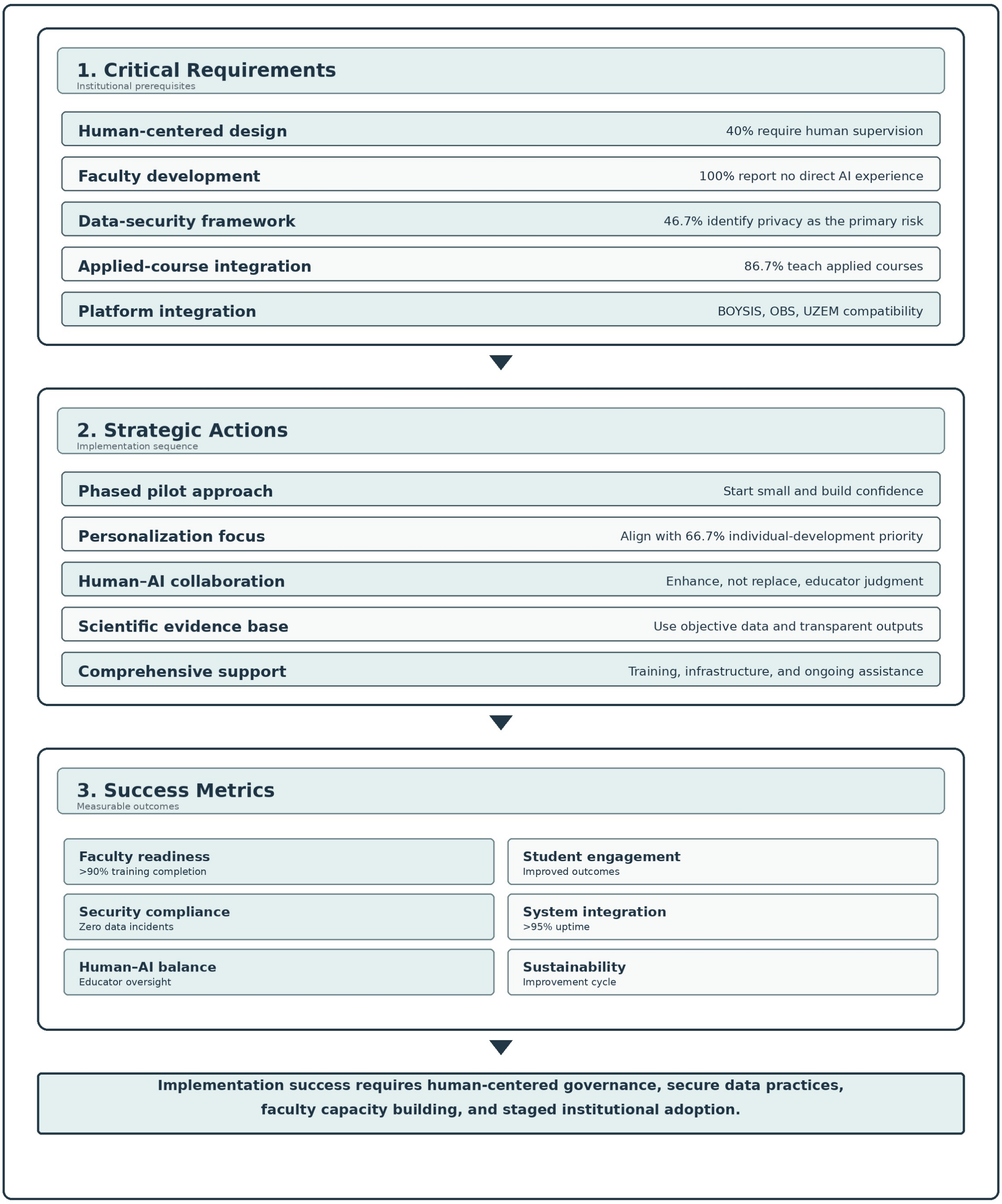

Figure 4. AISTSIM strategic implementation matrix.

8. Conclusions

This research demonstrates that academics in sports sciences education hold positive views towards AI-based intelligent training systems whilst maintaining sophisticated awareness of implementation challenges and ethical considerations. The study's contribution lies not only in documenting these perspectives but in translating them into a practical framework for implementation that respects human-centred educational values whilst leveraging technological capabilities for enhanced learning outcomes.

The predominant conceptualisation of intelligent training systems through individual development and personalisation (66.7%) reveals a mature understanding that prioritises pedagogical outcomes over technological sophistication. This human-centred perspective fundamentally shaped the AISTSIM model's development, ensuring that technological implementation serves educational goals rather than driving them. The finding that all participants lacked direct AI experience yet maintained positive attitudes suggests significant implementation potential when supported through appropriate training and infrastructure development.

The emphasis on scientific support and performance development (40%) demonstrates academics' commitment to evidence-based practice and readiness to adopt AI technologies that enhance rather than replace traditional pedagogical approaches. This scientific orientation, combined with the conditional acceptance requiring human supervision (40%), reflects professional responsibility and sophisticated understanding of AI limitations. The integration of these perspectives within the AISTSIM model ensures that technological advancement supports rather than undermines the fundamental elements of effective sports education.

The equal emphasis on holistic development evaluation and operational efficiency (both 40%) indicates that successful AI implementation must serve dual purposes: enhancing educational outcomes whilst improving institutional processes. The AISTSIM model addresses this dual requirement through comprehensive integration with existing educational platforms whilst providing enhanced analytical capabilities that support both student learning and institutional effectiveness. The model's development represents a systematic response to participant perspectives, incorporating identified benefits whilst addressing concerns through thoughtful design that maintains human-centred educational approaches.

8.1. Study limitations

This study's single-institution focus within the Turkish higher education context limits the generalisability of findings to other educational systems and cultural contexts. The research was conducted at Yozgat Bozok University with 15 participants from the Faculty of Sports Sciences, representing specific institutional and cultural perspectives that may not reflect broader international contexts or different institutional structures. The qualitative case study design, whilst providing rich insights into participant perspectives and enabling development of the AISTSIM model, cannot establish causal relationships between AI implementation and educational outcomes.

The absence of AI experience among all participants, whilst providing valuable insights into pre-implementation attitudes and readiness, limits understanding of actual usage challenges and benefits that emerge during system operation. The study captures perspectives about anticipated rather than experienced implementation, which may differ significantly from post-implementation realities. Additionally, the research focuses specifically on academic perspectives without incorporating student viewpoints, which represent a critical stakeholder group in educational technology implementation.

The reliance on qualitative methodology, whilst appropriate for exploring complex perspectives and developing theoretical frameworks, cannot provide quantitative measures of implementation effectiveness or comparative analysis of different implementation approaches. The study's emphasis on developing country contexts and specific integration requirements with Turkish educational platforms may limit applicability in different technological and regulatory environments.

More importantly, the model reflects perceptions from one institution and n = 15 academics, which constrains external validity and statistical generalisability. The sampling strategy targeted information power and meaning saturation rather than numerical representativeness; nevertheless, the findings should be read as context-specific and transferable only where institutional conditions are comparable [26, 27]. The model is currently unvalidated; its components should be treated as testable design propositions rather than confirmed effects.

8.2. Future research directions

The AISTSIM model requires extensive validation through longitudinal implementation studies that track actual deployment outcomes, student learning impacts, and faculty adaptation processes over extended periods. These studies should examine both intended and unintended consequences of AI integration whilst documenting best practices and implementation challenges that emerge during system operation. Cross-institutional validation studies examining AI integration across diverse educational settings would establish the model's broader applicability whilst identifying necessary adaptations for different institutional contexts.

Research priorities include investigating cultural and regulatory variations in AI adoption across different higher education systems, which would enhance the model's transferability beyond the Turkish context whilst maintaining sensitivity to local educational requirements. Comparative studies examining different implementation approaches would inform evidence-based decision-making about optimal strategies for AI integration in sports sciences education.

Mixed-methods research combining qualitative insights with quantitative performance measures would provide comprehensive understanding of AI implementation effectiveness whilst addressing the limitations of purely qualitative approaches. Student perspective studies examining learner experiences with AI-enhanced sports education would complement the faculty-focused insights generated through this research, providing holistic understanding of implementation impacts across all stakeholder groups.

The development of comprehensive metrics for measuring AI integration effectiveness in sports education contexts represents another critical research priority. These metrics should encompass not only academic performance outcomes but also student engagement, faculty satisfaction, institutional efficiency, and long-term educational impact measures that capture the multifaceted nature of successful AI implementation.

Future research should also examine the evolving relationship between AI capabilities and educational practice as technologies advance and institutional experience grows. The rapid pace of AI development necessitates ongoing research that ensures educational applications remain current with technological possibilities, whilst maintaining focus on pedagogical effectiveness rather than technological novelty. This research agenda would support the continued refinement and enhancement of the AISTSIM model whilst contributing to a broader understanding of AI integration in the higher education context.

8.3. Empirical validation pathway and key performance indicators

Future validation should proceed through staged empirical testing. First, a Delphi study with sports-science academics, educational technologists, AI specialists, ethics experts, and institutional learning-system administrators should be conducted to evaluate content validity and refine model components. Second, a small-scale pilot deployment should test one or two stages of AISTSIM in selected applied sports-science units. Third, usability testing should be conducted with academics and students to assess interpretability, workload impact, feedback usefulness, trust, and perceived fairness. Fourth, a longitudinal implementation study should examine learning outcomes, skill development, educator adoption, and institutional sustainability across multiple semesters and institutions.

Effectiveness should not be measured only through system adoption or technical performance. Because AISTSIM is a human-centred educational framework, evaluation should combine learning, governance, usability, ethics, and sustainability indicators. Table 14 presents indicative KPIs that may be refined during future validation.

Table 14. Indicative KPIs for evaluating successful AI integration under AISTSIM

KPI domain	Example indicators
Faculty readiness	Pre/post AI literacy scores; AI-TPACK self-efficacy; completion of training; confidence in interpreting AI outputs.
Pedagogical integration	Percentage of AI activities aligned with learning outcomes; number of assessments using human-interpreted AI evidence; rubric alignment quality.
Student learning	Improvement in practical skill performance; quality of reflective feedback use; student self-monitoring capacity; assessment performance.
Personalisation	Number of students receiving individualised feedback; quality of personalised development plans; student perception of relevance.
Human oversight	Frequency of educator review; AI recommendation override rate; documented reasons for overrides; moderation consistency.
Technical performance	System uptime; feedback latency; data completeness; LMS/student information system integration reliability.
Ethics and governance	Consent completion rate; privacy incident count; access-log audit completion; bias/fairness review outcomes.
Usability and acceptance	Student and staff usability scores; workload impact; trust in AI-supported feedback; perceived fairness.
Sustainability	Cost per student; staff support hours; scalability across courses; cross-semester continuity.
Safety in applied settings	Reduction in unsafe technique recurrence; timely identification of risk markers; educator-confirmed appropriateness of alerts.

Author contributions

Erol Baykan: Conceptualisation, methodology, formal analysis, investigation, data collection, writing - original draft, project administration. Ergun Gide: Supervision, methodology, translation oversight, validation, writing - review and editing. Mahmoud Elkhodr: Formal analysis, writing -

review and editing, visualisation, writing - recommendations and conclusions sections. All authors have read and approved the final manuscript.

Consent for publication

All participants provided informed consent for the publication of anonymised data. Individual participants cannot be identified from the published material, as all identifying information has been removed and participants are referenced through coded identifiers (A1-A15).

Data availability

The datasets generated and analysed during this research are not publicly available due to privacy and confidentiality considerations associated with qualitative interview data containing personal perspectives from identifiable academic staff. Requests for access to anonymised data supporting the conclusions of this article may be considered on reasonable request to the corresponding author, subject to appropriate ethical approval and data sharing agreements.

Use of Generative-AI tools declaration

An AI-assisted tool (Claude Sonnet 4, Anthropic) was used to assist with preparing an initial English translation from Turkish source materials. The translated output was reviewed, corrected, and expanded by the authors for terminology, meaning, disciplinary accuracy, and coherence with the coding framework. The AI tool was not used for participant recruitment, data collection, thematic coding, inter-coder reliability calculation, analysis, interpretation, or generation of research findings. Authorship, interpretation, and intellectual responsibility rest entirely with the authors.

Conflict of interest

The authors declare that they have no competing interests.

Professor Ergun Gide is an editorial board member of STEM Education and was not involved in the editorial review or the decision to publish this article.

Ethics declarations

Ethical approval for this research was obtained from the Social and Human Sciences Ethics Committee of Yozgat Bozok University on May 15, 2024, with decision number 25/147. All participants provided written informed consent prior to participation. The research was conducted in accordance with the principles outlined in the Declaration of Helsinki and adhered to institutional ethical guidelines for research involving human participants.

References

1. Cossich, V.R., Carlgren, D., Holash, R.J. and Katz, L., Technological breakthroughs in sport: Current practice and future potential of artificial intelligence, virtual reality, augmented reality,

and modern data visualization in performance analysis. *Applied Sciences,* 2023, 13(23): 12965. https://doi.org/10.3390/app132312965

2. Tuyls, K., Omidshafiei, S., Muller, P., Wang, Z., Connor, J., Hennes, D., et al., Game Plan: What AI can do for Football, and What Football can do for AI. *Journal of Artificial Intelligence Research,* 2021, 71: 41–88. https://doi.org/10.1613/jair.1.12505

3. Biró, A., Cuesta-Vargas, A.I. and Szilágyi, L., AI-controlled training method for performance hardening or injury recovery in sports. In *2024 IEEE 22nd World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, 2024, 000259–000264. IEEE. https://doi.org/10.1109/SAMI60510.2024.10432911

4. Goes, F.R., Meerhoff, L.A., Bueno, M.J.O., Rodrigues, D.M., Moura, F.A., Brink, M.S., et al., Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review. *European journal of sport science,* 2021, 21(4): 481–496. https://doi.org/10.1080/17461391.2020.1747552

5. Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., et al., Artificial intelligence: A powerful paradigm for scientific research. *The Innovation,* 2021, 2(4).

6. Mazurova, E. and Standaert, W., Implementing artificial intelligence across task types: constraints of automation and affordances of augmentation. *Information Technology & People,* 2024, 37(7): 2411–2440. https://doi.org/10.1108/ITP-11-2022-0915

7. Huang, Z., Wang, W., Jia, Z. and Wang, Z., Exploring the Integration of Artificial Intelligence in Sports Coaching: Enhancing Training Efficiency, Injury Prevention, and Overcoming Implementation Barriers. *Journal of Computer and Communications,* 2024, 12(12): 201–217. https://doi.org/10.4236/jcc.2024.1212012

8. Munoz-Macho, A.A., Domínguez-Morales, M.J. and Sevillano-Ramos, J.L., Performance and healthcare analysis in elite sports teams using artificial intelligence: a scoping review. *Frontiers in Sports and Active Living,* 2024, 6: 1383723. https://doi.org/10.3389/fspor.2024.1383723

9. Naughton, M., Salmon, P.M., Compton, H.R. and McLean, S., Challenges and opportunities of artificial intelligence implementation within sports science and sports medicine teams. *Frontiers in Sports and Active Living,* 2024, 6: 1332427. https://doi.org/10.3389/fspor.2024.1332427

10. Mateus, N., Abade, E., Coutinho, D., Gómez, M.Á., Peñas, C.L. and Sampaio, J., Empowering the sports scientist with artificial intelligence in training, performance, and health management. *Sensors,* 2025, 25(1): 139. https://doi.org/10.3390/s25010139

11. Zhu, W. and Li, J., Analysis and exploration on the integration of mental health education into college physical education practice. *Computational Intelligence and Neuroscience,* 2022, 2022(1): 5195909. https://doi.org/10.1155/2022/5195909

12. Elkhodr, M. and Gide, E., *Generative Artificial Intelligence Empowered Learning: A New Frontier in Educational Technology*, CRC Press, 2025. https://doi.org/10.1201/9781003422433

13. Elkhodr, M., Gide, E., Wu, R. and Darwish, O., ICT students' perceptions towards ChatGPT: An experimental reflective lab analysis. *STEM Education,* 2023, 3(2): 70–88. https://doi.org/10.3934/steme.2023006

14. Wangsa, K., Sandu, R., Karim, S., Elkhodr, M. and Gide, E., A systematic review and analysis on the potentials and challenges of genai chatbots in higher education. In *2024 21st International Conference on Information Technology Based Higher Education and Training (ITHET)*, 2024, 1–7. IEEE. https://doi.org/10.1109/ITHET61869.2024.10837608

15. Su, Z., Ge, S., Li, L. and Su, Y., Review study of integrating AI technology into sports training system. *Educ Adm Theory Pract,* 2024, 30(5): 7134–7140. https://doi.org/10.53555/kuey.v30i5.1649

16. Guo, R., Analysis of artificial intelligence technology and its application in improving the effectiveness of physical education teaching. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT),* 2024, 19(1): 1–15. https://doi.org/10.4018/IJWLTT.335115

17. Chu, H.C., Hwang, G.H., Tu, Y.F. and Yang, K.H., Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. *Australasian Journal of Educational Technology,* 2022, 38(3): 22–42.

18. Tunç, Z. and Baş, Ö., Analysis of studies based on Türkiye examining the relationship between artificial intelligence and education: A meta synthesis study. *İçtimaiyat,* 2024, 38–56. https://doi.org/10.33709/ictimaiyat.1532815

19. İçen, M., The future of education utilizing artificial intelligence in Turkey. *Humanities and Social Sciences Communications,* 2022, 9(1), article no. 268. https://doi.org/10.1057/s41599-022-01284-4

20. Masagca, R.C., The AI coach: A 5-week AI-generated calisthenics training program on health-related physical fitness components of untrained collegiate students. *Journal of Human Sport and Exercise,* 2025, 20(1): 39–56.

21. Wang, Y. and Wang, X., Artificial intelligence in physical education: comprehensive review and future teacher training strategies. *Frontiers in public health,* 2024, 12: 1484848. https://doi.org/10.3389/fpubh.2024.1484848

22. Bonilla, D.A., Sánchez-Rojas, I.A., Mendoza-Romero, D., Moreno, Y., Kočí, J., Gómez-Miranda, L.M., et al., Profiling physical fitness of physical education majors using unsupervised machine learning. *International Journal of Environmental Research and Public Health,* 2022, 20(1): 146. https://doi.org/10.3390/ijerph20010146

23. Li, S., Wang, C. and Wang, Y., Fuzzy evaluation model for physical education teaching methods in colleges and universities using artificial intelligence. *Scientific Reports,* 2024, 14(1): 4788. https://doi.org/10.1038/s41598-024-53177-y

24. Musat, C.L., Mereuta, C., Nechita, A., Tutunaru, D., Voipan, A.E., Voipan, D., et al., Diagnostic applications of AI in sports: a comprehensive review of injury risk prediction methods. *Diagnostics,* 2024, 14(22): 2516.

25. Reis, F.J., Alaiti, R.K., Vallio, C.S. and Hespanhol, L., Artificial intelligence and Machine Learning approaches in sports: Concepts, applications, challenges, and future perspectives. *Brazilian journal of physical therapy,* 2024, 28(3): 101083. https://doi.org/10.1016/j.bjpt.2024.101083

26. Yin, R.K., *Case study research: Design and methods*, sage, 2009.

27. Yıldırım, A. and Şimşek, H., Sosyal bilimler nitel araştırma yöntemleri (11. Baskı)[Social sciences qualitative research methods.] *Seçkin Yayıncılık,* 2018.

28. Hennink, M. and Kaiser, B.N., Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social science & medicine,* 2022, 292: 114523. https://doi.org/10.1016/j.socscimed.2021.114523

29. Bouncken, R.B., Czakon, W. and Schmitt, F., Purposeful sampling and saturation in qualitative research methodologies: recommendations and review. *Review of Managerial Science,* 2026, 20(2): 579–615. https://doi.org/10.1007/s11846-025-00881-2.

30. Creswell, J.W. and Poth, C.N., *Qualitative inquiry and research design: Choosing among five approaches*, Sage publications, 2016.

31. Chermack, T.J., *Scenario planning in organizations: how to create, use, and assess scenarios*, Berrett-Koehler Publishers, 2011.

32. Landis, J.R. and Koch, G.G., The measurement of observer agreement for categorical data. *Biometrics,* 1977, 33(1): 159–174. https://doi.org/10.2307/2529310

33. Mishra, P. and Koehler, M.J., Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record,* 2006, 108(6): 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

34. Blundell, C.N., Mukherjee, M. and Nykvist, S., A scoping review of the application of the SAMR model in research. *Computers and Education Open,* 2022, 3: 100093. https://doi.org/10.1016/j.caeo.2022.100093

35. Miao, F. and Cukurova, M., *AI Competency Framework for Teachers*, Paris, France: UNESCO, 2024.

36. Alfredo, R., Echeverria, V., Jin, Y., Yan, L., Swiecki, Z., Gašević, D., et al., Human-centred learning analytics and AI in education: A systematic literature review. *Computers and Education: Artificial Intelligence,* 2024, 6: 100215. https://doi.org/10.1016/j.caeai.2024.100215

37. Ning, Y., Zhang, C., Xu, B., Zhou, Y. and Wijaya, T.T., Teachers' AI-TPACK: Exploring the relationship between knowledge elements. *Sustainability,* 2024, 16(3): 978. https://doi.org/10.3390/su16030978

38. Elkhodr, M. and Gide, E., The SAGE framework for developing critical thinking and responsible generative AI use in cybersecurity education. *Discover Education,* 2025, 4: article no. 517. https://doi.org/10.1007/s44217-025-00935-3

Author's biography

Dr. Erol Baykan is a faculty member at the Faculty of Sport Sciences, Yozgat Bozok University, Türkiye. His research interests encompass sport management, artificial intelligence applications, digital transformation, sport technologies, higher education, sport policy, and qualitative research methodologies.

Dr. Ergun Gide is a Professor in the School of Engineering and Technology at Central Queensland University, Australia. His research and teaching interests include AI, project management, digital transformation, higher education, and technology-enhanced learning.

Dr. Mahmoud Elkhodr is a Senior Lecturer in the School of Engineering and Technology at Central Queensland University, Australia. His research focuses on cybersecurity, the Internet of Things, artificial intelligence, digital health, smart cities, and technology-enhanced education.

AIMS Press