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Digital Readiness and Institutional Constraints: Artificial Intelligence in Hungarian Physical Education Teacher Education

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Abstract

The diffusion of artificial intelligence (AI) is reshaping higher education, yet its integration into practice-oriented teacher education remains uneven. This cross-sectional study examined the AI-related attitudes, knowledge, usage habits, and prospective application intentions of pre-service physical education (PE) teachers in Hungary. Data were collected during the autumn semester of 2025/2026 using the MIATT 2024_rev online questionnaire across seven Hungarian universities offering PE teacher education (N = 416). Principal component analysis (PCA; KMO = 0.741; Bartlett's test, $p < 0.001$) yielded two components—communicative–interpretive (PC1) and performance–developmental (PC2)—jointly accounting for 51.7% of the variance; internal consistency was acceptable (Cronbach's $\alpha = 0.693$). Respondents rated sport performance analysis (73.3%) as the most relevant pedagogical application of AI; only 7.7% expressed career-displacement concerns. Satisfaction with institutional AI provision was moderate (M = 2.85, SD = 0.85), and knowledge gaps (27.6%) and funding constraints (25.5%) emerged as principal barriers. Part-time and master's-level students reported significantly greater interest in AI-related coursework than full-time and undivided programme counterparts ($p < 0.001$), and institutional satisfaction correlated positively with course interest ($\rho = 0.192$, $p < 0.01$). Overall, student receptivity outpaces perceived institutional provision, indicating a need for system-level AI integration in PE teacher education.

Keywords: artificial intelligence; educational technology; sport pedagogy; digital competence; higher education curriculum

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1. Introduction

Artificial intelligence (AI) is among the most rapidly developing technological domains of the present era, with its fields of application expanding at an unprecedented rate (Tang et al., 2020). As a consequence, AI is penetrating everyday life, multiple scientific disciplines, and the structural processes of the labour market with increasing depth. Its emergence is not merely a technological development but a broader social and educational challenge that compels a reconsideration of how knowledge is transmitted, how competences are cultivated, and how professionals are trained. It is therefore increasingly evident that higher education in general—and teacher education in particular—cannot remain insulated from the implications of AI diffusion. A central responsibility of teacher education is to prepare future educators for the pedagogically informed, effective, and critical integration of AI into their professional practice. This responsibility is especially pronounced in disciplines such as sport science and physical education (PE), where practical skill acquisition, embodied learning, and technological innovation converge.

The growing presence of AI technologies in sport science and PE is well documented. The investigation of the complex applications of AI in PE has therefore become an active and continuing research agenda (Zhou et al., 2024), and AI in physical education (AIPE) has attracted considerable scholarly attention (Lee & Lee, 2021; Malik et al., 2019). Within PE, AI-based technologies—motion-analysis systems, wearable devices, and intelligent feedback applications—offer substantial potential to transform conventional pedagogical practice through individualised learning, more objective assessment, and data-informed decision-making. Wang and Wang (2024) identified four dominant application areas: performance analysis and prediction, individualised training planning, injury-prevention monitoring, and the enhancement of learner motivation. In the broader coaching context, Huang et al. (2024) described a three-phase guidance–monitoring–correction model in which experience-based coaching decisions are augmented by data-driven processes, with demonstrable improvements in training efficiency and athletic performance. A systematic review by Bofill et al. (2025) further confirmed that AI-based motion analysis and feedback systems can enhance not only the accuracy of technical performance but also learner motivation and the objectivity of assessment. In a complementary review of education more broadly, Chen et al. (2020) identified four principal application areas: intelligent tutoring systems, adaptive learning platforms, automated assessment systems, and teacher decision-support tools. Coupled with the embodied, performance-oriented character of PE, these approaches outline a particularly promising—though still under-explored—integration pathway (Wang & Wang, 2024).

AI adoption among PE teachers is, nevertheless, constrained by a complex configuration of barriers. Wang and Wang (2024) reported that many practitioners disclose fundamental knowledge gaps in operating AI tools, while some perceive AI as a threat to their professional role. Rajki et al. (2024) similarly emphasised that, in the absence of clearly identified integration opportunities and an assessment of individual needs, AI use tends to remain superficial. Comparative analyses by Rajki et al. (2024) and Nagy et al. (2025) further indicate that the most common barriers to AI adoption by teachers—insufficient training, infrastructural constraints, ethical concerns, and a perceived mismatch between AI tools and pedagogical purposes—are strongly context-dependent and surface with different priorities across developing and developed education systems.

Social Cognitive Theory (SCT; Bandura, 1986) offers a complementary lens by emphasising that human behaviour—including technology adoption—is shaped by the reciprocal interaction of personal cognitive factors, behavioural enactment, and environmental influences. In educational contexts, SCT highlights the role of self-efficacy beliefs and observational learning in determining whether individuals engage with new technologies, including AI tools.

Within teacher education more broadly, the Technology Acceptance Model (TAM) has become a widely adopted framework for examining AI uptake. Drawing on a sample of pre-service teachers, Alejandro et al. (2024) demonstrated that perceived usefulness and attitude are the two strongest predictors of intention to use AI in teaching. With reference to AI-assisted training, Zhang and Sun (2026) reported that AI-assisted training is positively associated with sport performance among university student-athletes through both cognitive–technical and psychological pathways, providing empirical support for the integration of AI into PE teacher education. Applying a combined SCT-TAM framework in a cross-national context, Le Xiu et al. (2026) further demonstrated that the relationship between institutional support and AI literacy is non-linear, with some teachers developing sophisticated competencies despite limited institutional backing—a finding that points to

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the complexity of AI adoption in educational contexts. Building on this dual framework, the present study adopts a combined TAM-SCT perspective to examine how individual attitudes and perceived institutional conditions associated with AI integration readiness. Because the instrument does not directly measure self-efficacy, the application of SCT in the present study is necessarily partial and exploratory.

Cognate, application-oriented training fields—most notably in the health professions—reveal a similar dual pattern. The qualitative study by Rony et al. (2024) with nurse practitioners showed that participants held moderately positive attitudes toward AI yet possessed limited practical knowledge, and they highlighted the need for comprehensive training, ethical guidance, and organisational support. Among health-care professionals more broadly, Dai et al. (2025) identified knowledge gaps, ethical uncertainty, and weak organisational support as the three most critical barriers—a configuration that closely parallels the situation in PE teacher education.

Within the Hungarian context, the integration of AI into PE teacher education remains largely unexplored. The pilot study (Varga & Fügedi, 2025), on which the present work builds, reported that PE student teachers' AI-related knowledge is expanding, but the substantive integration of AI into practice-based training remains limited, with both institutional strategy and instructor support lagging behind. Among Hungarian higher-education students more generally, AI tool use is widespread but typically concentrated on one or two tools, and critical reflection is comparatively low. From the instructor perspective, Nagy et al. (2025) likewise documented substantial differences in access and attitudes between institutions and training formats.

Despite growing international literature on AI in education, empirical studies that specifically address the perspective of prospective PE teachers remain limited, particularly in Central and Eastern Europe. The present study aims to address this gap by reporting findings from a large-sample, cross-sectional empirical investigation focused on PE student teachers' AI attitudes, knowledge, and institutional experiences. The findings are intended to provide a relevant evidence base for the design of teacher training programmes, the formulation of institutional AI strategies, and policy decision-making, including from an international comparative perspective.

Despite documented evidence that AI technologies offer transformative potential for physical education pedagogy, it remains poorly understood why perceived limitations in institutional AI provision consistently lag behind student-level receptivity in PE teacher education. Existing studies have largely examined AI adoption through single-factor models—focusing on attitudes, barriers, or knowledge in isolation—without investigating how the interplay between individual technology acceptance and institutional support structures jointly shapes AI integration competences among prospective PE teachers. This gap is particularly acute in Central and Eastern Europe, where the socio-institutional context diverges substantially from the settings in which TAM- and SCT-based frameworks have predominantly been validated. The present study addresses this problem by examining the attitudes, knowledge levels, and institutional experiences of Hungarian pre-service PE teachers within a nationally comprehensive and institutionally inclusive, cross-sectional design (Table 1).

Table 1. Analytical constructs, operationalisation, and hypothesised relationships.

Construct	Role in Study	Operationalisation	Hypothesised Relationship
AI attitude	Dependent (H1a)	Seven-item Likert scale measuring beliefs about AI capabilities (Block 2, item 7); two-component structure: communicative–interpretive (PC1) and performance–developmental (PC2)	Pre-service PE teachers hold positive overall AI attitudes; communicative–adaptive capabilities rated more favourably than autonomous decision-making
AI knowledge and experience	Dependent (H1b)	Self-reported familiarity and usage of AI tools; five-point scale and checklist (Block 3, items 8–15)	Positive attitude does not co-occur with high practical knowledge, indicating a receptivity–preparedness gap
AI-course interest	Dependent (H2, H3)	Single four-point item assessing motivation for formal AI-focused training (Block 4, item 17)	Higher in part-time and master's-level students (H2); positively associated with institutional satisfaction (H3)
Institutional AI satisfaction	Independent/correlate (H3, H4)	Single four-point item assessing perceived quality of institutional AI provision (Block 4, item 16)	Positively related to AI-course interest (H3); no gender differences in AI attitudes or interest (H4)

Note. TAM = Technology Acceptance Model; SCT = Social Cognitive Theory. H1a–H4 refer to the study hypotheses. Block numbers correspond to sections of the MIATT 2024_rev questionnaire.

Study Objectives and Hypotheses

The primary aim of the study was to provide an empirical account of the AI-related knowledge, attitudes, usage habits, and prospective application intentions of pre-service PE teachers in Hungary. A secondary aim was to identify associations between sociodemographic characteristics—training format, programme type, institution, gender, and year of study—and students' AI attitudes and interest, in order to inform AI-integration strategies in PE teacher education.

Five hypotheses were tested:

H1a. *Pre-service PE teachers hold generally positive attitudes toward AI, rating its communicative and adaptive capabilities (e.g., natural language understanding, feedback-based learning) more favourably than its autonomous decision-making capabilities, as measured by the seven-item AI attitude scale (questionnaire Block 2).*

H1b. *This positive attitude does not coincide with high practical knowledge of AI tools or high institutional satisfaction with AI provision, indicating a receptivity–preparedness gap at the individual–institutional interface, operationalised through the AI knowledge level item (Block 3) and the institutional satisfaction item (Block 4, item 16).*

H2. *Part-time and master's-level students demonstrate significantly greater interest in AI-focused coursework than full-time and undivided teacher education programme students, a difference potentially associated with labour-market experience, as assessed by the AI-course interest item (questionnaire Block 4, item 17), compared across training format and programme type (Block 1, items 4–5).*

H3. *Institutional AI satisfaction and AI-course interest are positively associated, such that higher institutional AI satisfaction is associated with greater interest in formal competence development, operationalised through the institutional AI satisfaction item (Block 4, item 16) and AI-course interest item (Block 4, item 17), analysed via Spearman rank-order correlation.*

H4. *There are no significant gender differences in AI attitudes or interest: male and female PE student teachers display comparable AI receptivity, contrary to common generalisations regarding a gendered digital divide, tested using Mann–Whitney U comparisons of the AI attitude scale scores and the AI-course interest item across gender (Block 1, item 1).*

The following null hypotheses (H0) were formulated to frame the inferential analyses: $H0_{1a}$: Pre-service PE teachers' attitudes towards AI's communicative–interpretive capabilities do not differ from their attitudes towards its performance–developmental capabilities. $H0_{1b}$: AI attitude and self-reported AI knowledge do not co-occur at high levels in the same individuals. $H0_2$: Interest in AI-related coursework does not differ between training formats (full-time vs. part-time) or programme types (undivided vs. master's). $H0_3$: There is no significant association between institutional AI satisfaction and interest in AI-related coursework. $H0_4$: There are no significant differences between male and female students in AI attitudes or interest in AI-related coursework. Significance testing was employed as a conventional decision rule; statistical decisions are reported with exact *p*-values throughout.

2. Method

2.1. Participants and Procedure

A total of 416 pre-service PE teachers from the seven Hungarian higher-education institutions that offer PE teacher education participated in the study (Table 2). Data collection was conducted using the MIATT 2024_rev (Mesterséges Intelligencia és Adaptációja a Testnevelő Tanárképzésben; Artificial Intelligence (AI) and Its Adaptation in Physical Education Teacher Training) online questionnaire during the 2025/2026 academic year, autumn semester, distributed via institutional coordinators. Participation was voluntary and anonymous. The instrument was developed from the earlier pilot study (Varga & Fügedi, 2025); the MIATT_2024 pilot version was adapted to the specific characteristics of PE teacher education (MIATT_2024_rev) following reliability checks (Cronbach's α) and pre-testing. The study adopted a census approach at the institutional level: all seven Hungarian higher-education institutions offering PE teacher education were included, and questionnaires were distributed to all enrolled students at each site. Within each institution, however, participation depended on voluntary completion, so the effective sample reflects a convenience procedure rather than a guaranteed census. According to the FIR/FIRSTAT student enrolment statistics maintained by the Hungarian Educational Authority, the target population in the autumn semester of the 2025/2026 academic year comprised 2054 active students enrolled in physical education teacher education programmes at the seven participating institutions. For ELTE, only students enrolled at the Szombathely training site were included, in line with the sampling frame of the study. Based on 416 valid responses, the estimated overall response rate was 20.3%, with institution-level response rates ranging from 6.9% (MTSE) to 46.9% (EKKE) (Table 3). The findings should be interpreted in light of this participation rate and the voluntary nature of the survey.

Table 2. Demographic characteristics of the study sample (N = 416).

Variable	Category	*n*	%
Gender	Male	255	61.3
	Female	161	38.7
Programme	Undivided teacher education programme *	259	62.3
	Master's programme	157	37.7
Training format	Full-time	234	56.2
	Part-time	182	43.8
Year of study	1st	239	57.5
	2nd	63	15.1
	3rd	43	10.3
	4th–6th	71	17.1
Institution	EKKE, Eger	152	36.5
	SZTE, Szeged	74	17.8
	DE, Debrecen	59	14.2
	MTSE, Budapest	47	11.3
	PTE, Pécs	32	7.7
	ELTE, Szombathely	29	7.0
	NYE, Nyíregyháza	23	5.5

Note. EKKE = Eszterházy Károly Catholic University; SZTE = University of Szeged; DE = University of Debrecen; MTSE = Hungarian University of Sports Science; PTE = University of Pécs; ELTE = Eötvös Loránd University (Szombathely campus); NYE = University of Nyíregyháza. * In the Hungarian context, undivided teacher education refers to a long-cycle integrated teacher education programme that leads directly to a teaching qualification without a separate bachelor's and master's phase.

Table 3. Target population and estimated response rates by institution (FIR/FIRSTAT).

Institution	Undivided	Master's	Target Population	*n*	Response Rate
EKKE	147	177	324	152	46.9%
SZTE	94	107	201	74	36.8%
DE	262	14	276	59	21.4%
MTSE	511	168	679	47	6.9%
PTE	109	140	249	32	12.9%
ELTE [a]	161	51	212	29	13.7%
NYE	68	45	113	23	20.4%
Total	1352	702	2054	416	20.3%

Note. Data source: FIR/FIRSTAT (Hungarian Educational Authority), "Hallgató 2025/26 ősz" enrolment table; reference date: 15 October 2025 (https://firstat.oh.gov.hu/letoltheto-adatok). Target population includes students enrolled in undivided (osztatlan) and master's-level physical education teacher education programmes. [a] ELTE data restricted to Szombathely training site only, in line with the sampling frame of the present study. EKKE = Eszterházy Károly Catholic University; SZTE = University of Szeged; DE = University of Debrecen; MTSE = Hungarian University of Sports Science; PTE = University of Pécs; ELTE = Eötvös Loránd University (Szombathely campus); NYE = University of Nyíregyháza.

2.2. Ethical Approval

The study was conducted in accordance with the principles of the Declaration of Helsinki. Institutional ethics approval was obtained from the institutional ethics committee (approval no. RK/265/2026). No personally identifying information was collected.

2.3. Instrument

The MIATT 2024_rev questionnaire comprised five thematic blocks. Block 1 (items 1–6) collected sociodemographic data (gender, age, institution, programme type, study mode, and year of study). Block 2 (item 7, seven sub-items) measured AI attitudes using a four-point Likert scale (1 = strongly disagree, 4 = strongly agree), capturing beliefs about the cognitive, adaptive, and decision-making capabilities of AI; a representative item was: "AI is capable of imitating human thinking." Block 3 (items 8–15) assessed AI knowledge and experience through a five-point familiarity scale (1 = never heard of it, 5 = use it regularly) and checklist items, for example: "What level of experience do you have with text and content generation tools (e.g., ChatGPT, Gemini)?" Block 4 (items 16–18) captured institutional satisfaction and course interest on four-point scales—e.g., "How satisfied are you with the way your university integrates modern artificial intelligence tools into educational practice?" (1 = not satisfied at all, 4 = completely satisfied)—alongside perceived barriers to AI use (checklist). Block 5 (items 19–30) examined risk perception, career impact, and application domains using four-point Likert scales and nominal response items. Items in the present analysis draw primarily on Blocks 2 and 4, with supplementary descriptive data from Block 5.

Four constructs guided the analysis: (1) AI attitude, operationalised as beliefs about AI capabilities (Block 2); (2) AI knowledge and experience, captured through self-reported familiarity and usage of AI tools (Block 3); (3) institutional AI satisfaction, reflecting perceived quality of institutional AI provision (Block 4, item 16); and (4) AI-course interest, indicating motivation for formal AI competence development (Block 4, item 17). These constructs were not hypothesised to form a single latent factor; rather, the study examined their descriptive profiles and selected bivariate associations—specifically the relationship between institutional satisfaction and course interest (H3), and between sociodemographic variables and course interest (H2)—within an exploratory cross-sectional design informed by TAM and SCT.

2.4. Statistical Analysis

Statistical analyses comprised descriptive statistics (means, standard deviations, frequencies), Mann–Whitney U tests for the comparison of two independent groups, Kruskal–Wallis H tests for the comparison of more than two independent groups, and Spearman's rank-order correlations. Prior to analysis, the normality of all continuous and ordinal variables was assessed using the Shapiro–Wilk test. All variables departed significantly from a normal distribution (W = 0.798–0.902, $p < 0.001$ for all), confirming that the assumption of normality was not met and justifying the use of nonparametric inferential procedures throughout. Although Likert-type responses are technically ordinal, means and standard deviations are reported alongside nonparametric test results, as this practice is widely accepted in the social sciences (Norman, 2010; Sullivan & Artino, 2013) and facilitates substantive interpretation of item-level differences; the statistical decisions were, however, based exclusively on nonparametric tests. The dimensionality of the AI attitude scale was explored using principal component analysis (PCA; varimax rotation and Kaiser normalisation). Sample adequacy was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity (KMO = 0.741; Bartlett's test: $\chi^2 = 446.26$, df = 21, $p < 0.001$), both indicating that the correlation matrix was suitable for component analysis. Two components with eigenvalues exceeding unity were retained (Kaiser criterion): PC1 ($\lambda = 2.48$, 35.4% of variance) and PC2 ($\lambda = 1.14$, 16.3% of variance), jointly accounting for 51.7% of the total variance (pre-rotation eigenvalue-based; post-rotation SS loading-based values: PC1 = 26.4%, PC2 = 25.4%, total = 51.7%—see Table A1). The complete rotated component matrix, including factor loadings and communalities, is presented in

Table A1 (Appendix A). The internal consistency of the scale was subsequently assessed; Cronbach's α = 0.693 was obtained. Subscale reliability estimates were as follows: α = 0.440 for PC1 (communicative–interpretive; three items) and α = 0.623 for PC2 (performance–developmental; four items), indicating that PC2 shows adequate internal consistency while PC1 should be interpreted with caution given its low subscale alpha. An alpha of 0.440 for PC1 represents weak internal consistency, not a marginal shortfall. PC1 should not be treated as a robust subscale; component-level findings should be regarded as exploratory and interpreted with considerable caution (Hair et al., 2019). The significance threshold was set at $p < 0.05$. Given the number of exploratory comparisons conducted beyond the prespecified primary hypothesis tests, isolated findings—particularly those with p-values near the threshold (e.g., $p = 0.032$) or weak effect sizes (e.g., $\rho \approx 0.10$)—should be interpreted with caution as potentially susceptible to Type I error. All analyses were performed using IBM SPSS Statistics 29.0.

3. Results

3.1. Structure and Level of AI Attitudes

Students' attitudes toward AI capabilities were measured using a seven-item, four-point Likert scale. The item "improves on the basis of feedback" received the highest mean (M = 3.15, ±SD = 0.71), followed by "interprets human communication" (M = 3.08, ±SD = 0.72) and "surpasses human performance" (M = 3.03, ±SD = 0.87). By contrast, the item "always makes the right decision" received the lowest mean (M = 1.75, ±SD = 0.74), indicating that students hold a critical and realistic view of AI's decision-making limits (Table 4).

Table 4. Items of the AI attitude scale: response distribution and descriptive statistics (N = 416).

Attitude Statement	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree	M	±SD
Can imitate human thinking	45 (10.8%)	154 (37.0%)	169 (40.6%)	48 (11.5%)	2.53	0.84
Can solve complex problems	27 (6.5%)	126 (30.3%)	182 (43.8%)	81 (19.5%)	2.76	0.84
Always makes the right decision	174 (41.8%)	177 (42.5%)	60 (14.4%)	5 (1.2%)	1.75	0.74
Surpasses human performance	21 (5.0%)	89 (21.4%)	164 (39.4%)	142 (34.1%)	3.03	0.87
Always understands instructions accurately	94 (22.6%)	221 (53.1%)	91 (21.9%)	10 (2.4%)	2.04	0.74
Improves on the basis of feedback	6 (1.4%)	59 (14.2%)	218 (52.4%)	133 (32.0%)	3.15	0.71
Interprets human communication	9 (2.2%)	66 (15.9%)	222 (53.4%)	119 (28.6%)	3.08	0.72

Note. Four-point Likert scale (1 = strongly disagree, 4 = strongly agree). M = mean; ±SD = standard deviation. Cronbach's α = 0.693. N = 416.

3.2. Application Areas and Barriers

In Question 30, respondents identified sport performance analysis (73.3%) as the most relevant pedagogical application of AI in PE, followed by VR/AR-based learning experiences (45.4%), personalised health promotion (42.1%), rehabilitation (36.3%), and virtual training systems (32.2%; Table 5). Regarding AI's future role in sport, 33.7% of students viewed AI as having a "significant impact across multiple areas" and 28.4% described it as "drastically transformative," whereas 21.4% reported uncertainty; only 7.7% expressed concern that AI could negatively affect the teaching labour market.

Table 5. Distribution of AI application areas and barriers (N = 416).

Application Area/Barrier	*n*	%
Question 30—Most useful areas of AI in physical education		
Sport performance analysis	305	73.3
Enhanced learning experience (VR, AR)	189	45.4
Personalised health promotion	175	42.1
Rehabilitation and physiotherapy	151	36.3
Virtual training systems	134	32.2
Question 18—Barriers to AI application		
No perceived barrier	151	36.3
Knowledge gaps in AI	115	27.6
Funding constraints	106	25.5
Ethical concerns	89	21.4
Data-protection concerns	64	15.4

Note. Percentages sum to more than 100% because the items permitted multiple responses. N = 416.

Question 18, addressing barriers, indicated that 36.3% of students perceived no obstacle to AI use. Within the remaining two-thirds of the sample, the most prominent barriers were knowledge gaps (27.6%), funding constraints (25.5%), ethical concerns (21.4%), and data-protection concerns (15.4%). This pattern aligns with three critical dimensions highlighted in UNESCO's educational AI framework: knowledge gaps, inequality of access, and ethical responsibility (UNESCO, 2021).

3.3. Between-Group Differences

Comparison by training format revealed a significant difference in interest in AI-related coursework: part-time students (M = 3.42, ±SD = 0.74) reported significantly higher interest than full-time students (M = 2.96, ±SD = 0.95), U = 15581.0, $p < 0.001$, r = 0.23. A similar pattern emerged for programme type: master's students (M = 3.48, ±SD = 0.68) expressed significantly greater interest than students in the undivided teacher education programme (M = 2.97, ±SD = 0.95), U = 14283.0, $p < 0.001$, r = 0.25. A significant difference by training format was also observed for the attitude item "AI can imitate human thinking" (full-time: M = 2.45 vs. part-time: M = 2.63; U = 18850.0, $p = 0.032$, r = 0.10).

The Kruskal–Wallis H test revealed significant institutional differences in interest in AI-related coursework (H = 23.52, $p = 0.001$, $\eta^2 = 0.043$), institutional satisfaction (H = 13.63, $p = 0.034$, $\eta^2 = 0.019$), and the appraisal of AI's interpretive capability (H = 16.89, $p = 0.010$, $\eta^2 = 0.027$). EKKE led the ranking on AI-course interest (M = 3.36), followed by MTSE (M = 3.28) and SZTE (M = 3.18), with ELTE showing the lowest mean (M = 2.59). Dunn post hoc comparisons (Bonferroni-corrected) identified three significant pairwise differences for AI-course interest: EKKE vs. ELTE ($p = 0.001$), EKKE vs. DE ($p = 0.032$), and MTSE vs. ELTE ($p = 0.047$). For AI interpretive capability, one significant pair emerged: EKKE vs. ELTE ($p = 0.005$). For institutional satisfaction, no pairwise differences survived Bonferroni correction, suggesting that the overall group effect reflects a distributed rather than localised pattern. No significant gender differences were observed for any of the variables examined ($p > 0.05$ in all comparisons) (Table 6).

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Table 6. Significant and non-significant between-group comparisons (N = 416).

Dependent Variable	Grouping	Group 1: M (±SD)	Group 2: M (±SD)	Test	*p*
Interest in AI-related course	Training format	Full-time: 2.96 (±0.95)	Part-time: 3.42 (±0.74)	U = 15,581.0	<0.001
Interest in AI-related course	Programme	Single-cycle: 2.97 (±0.95)	Master's: 3.48 (±0.68)	U = 14,283.0	<0.001
AI—imitating human thinking	Training format	Full-time: 2.45 (±0.81)	Part-time: 2.63 (±0.86)	U = 18,850.0	0.032
Satisfaction (AI in education)	Institution	EKKE: 3.07/ELTE: 2.52	—	H = 13.63	0.034
Interest in AI-related course	Institution	EKKE: 3.36/ELTE: 2.59	—	H = 23.52	0.001
AI—interpretive capability	Institution	Differences across institutions	—	H = 16.89	0.010
Interest in AI-related course	Gender	Male: 3.18 (±0.89)	Female: 3.12 (±0.91)	U = 20,341.5	0.412

Note. M = mean; ±SD = standard deviation; U = Mann–Whitney U; H = Kruskal–Wallis H. $p < 0.05$ indicates statistical significance. N = 416. None of the gender comparisons reached statistical significance ($p > 0.05$).

3.4. Correlational Patterns

Spearman's rank-order correlation analysis revealed a significant positive association between institutional AI satisfaction and interest in AI-related coursework (ρ = 0.192, $p < 0.01$). AI knowledge level showed weak but significant relations with course interest (ρ = 0.101, $p < 0.05$) and with a more favourable appraisal of AI's capacity to surpass human performance (ρ = 0.110, $p < 0.05$). Satisfaction was also significantly positively related to belief in AI's capacity to imitate human thinking (ρ = 0.164, $p < 0.01$). The attitude items themselves were positively and significantly intercorrelated (ρ = 0.191–0.267, $p < 0.01$), supporting the internal coherence of the construct (Table 7).

Table 7. Spearman's rank-order correlation matrix among key variables (N = 416).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AI knowledge level	—	0.032	0.101 *	0.025	0.110 *	0.077	0.060
(2) Satisfaction		—	0.192 **	0.164 **	−0.013	0.052	0.106 *
(3) Interest in AI-related course			—	0.111 *	0.173 **	0.182 **	0.162 **
(4) AI—imitating human thinking				—	0.212 **	0.191 **	0.234 **
(5) AI—surpassing human performance					—	0.262 **	0.229 **
(6) AI—improving with feedback						—	0.267 **
(7) AI—interpretive capability							—

Note. Spearman's rank-order correlations. ** $p < 0.01$; * $p < 0.05$. N = 416.

4. Discussion

4.1. Student Receptivity and Its Limits

The data describe a dual picture. Students do not merely consume AI technology but assign particularly high relevance to it in sport performance analysis (73.3%). Wang and Wang (2024) similarly report that PE teachers regard performance analysis and movement feedback as the most useful applications of AI. The data-informed training model proposed by Huang et al. (2024) points in the same direction: pre-service PE teachers recognise that data-based optimisation of training is both relevant and practically accessible.

A degree of cognitive realism is also evident in the responses. Doubt about AI's capacity for "perfect decision-making" (M = 1.75, ±SD = 0.74) suggests that students do not idealise the technology. Bofill et al.'s (2025) systematic review likewise emphasises that, in PE, AI complements rather than replaces the teacher's pedagogical judgement. The fact that only 7.7% of respondents reported career-related concerns reinforces this interpretation: pre-service PE teachers appear to identify embodied interaction and the value of live human contact as competences for which AI cannot substitute.

At the same time, a gap is apparent between student receptivity and the level of institutional provision reported by respondents. The moderate mean satisfaction with institutional AI provision (M = 2.85, ±SD = 0.85) and the prominence of knowledge gaps as the leading barrier (27.6%) suggest that, as perceived by the students surveyed, institutional provision has not yet kept pace with student interest—though this interpretation rests on self-reported perceptions rather than an independent assessment of institutional readiness and warrants further investigation. This pattern is not unique to the Hungarian setting: Nagy et al.'s (2025) comparative analysis suggests that teacher education programmes worldwide are struggling with the substantive curricular integration of AI, and that perceived institutional provision typically lags behind student interest.

4.2. The Role of Education Format and Programme Type

The significantly higher AI interest of part-time and master's-level students ($p < 0.001$) may reflect the joint influence of several factors. First, this pattern is consistent with, though not directly attributable to, greater professional contextualisation among these student groups: students with labour-market experience may be better positioned to relate AI to their professional reality, potentially engaging with it as a concrete workplace tool rather than as an abstract technology. Within the TAM framework, Alejandro et al. (2024) demonstrated that perceived usefulness is the strongest predictor of AI adoption; work experience may reinforce this perception, although labour-market experience was not directly measured in the present study.

Second, master's-level students may be more inclined to reflect on their own digital competence gaps and to seek the knowledge offered by formal training in a more focused manner. More advanced students may tend to engage with AI tools more critically and selectively than first-year, full-time students, whose responses may reflect general curiosity rather than deeper professional motivation—though these remain possible explanations for the observed group differences rather than directly measured findings. The institutional differences observed (EKKE vs. ELTE: ΔM = 0.77) further suggest that institutional curricular and infrastructural contexts may be associated with the level of interest (Nagy et al., 2025), a pattern consistent with Le Xiu et al.'s (2026) cross-national finding that institutional context and AI competence are related in a complex, non-linear manner.

4.3. Gender and AI Attitudes: The Absence of a Digital Divide

The absence of significant gender differences across all comparisons ($p > 0.05$) runs counter to the generalisations common in digital-technology research. Rather than the male dominance often assumed in STEM and digital domains, the present data indicate that female and male PE student teachers in Hungary respond to AI with comparable receptivity. This pattern may reflect, in part, the specific character of the sample: PE student teachers of both genders share a strong sport-practice orientation, within which performance analysis and feedback technologies carry gender-neutral relevance. Consistent with this interpretation, Zhang and Sun (2026) reported no gender differences in the acceptance of AI-assisted training among university student-athletes, consistent with the absence of significant gender differences observed in the present study.

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4.4. Correlation as a Developmental Direction

The positive correlation between institutional AI satisfaction and AI-course interest ($\rho = 0.192$, $p < 0.01$) suggests a positive association: students who report higher-quality institutional AI provision also tend to report greater motivation for further competence development. This pattern is consistent with the TAM of Alejandro et al. (2024), in which institutional AI experience is associated with perceived usefulness and, in turn, application intention. The observation that AI knowledge level is only weakly—though significantly—related to interest ($\rho = 0.101$, $p < 0.05$) cautions against equating information delivery with competence building: pedagogical approaches grounded in positive experience and attitude formation may prove more effective (Chen et al., 2020).

4.5. International and Cross-Disciplinary Parallels

A similar pattern—students reporting high receptivity alongside perceived limitations in institutional AI provision—has been documented in cognate fields. Rony et al.'s (2024) systematic findings in nursing and Dai et al.'s (2025) study in health-care training identify a comparable configuration of student openness and perceived institutional unpreparedness. Whether this reflects a broader system-level rather than sector-specific phenomenon warrants further cross-national and longitudinal investigation. UNESCO's (2021) Recommendation on the Ethics of Artificial Intelligence addresses precisely this direction, urging training institutions to integrate AI in ways that are ethically grounded, equitable, and competence-building.

4.6. Evaluation of the Hypotheses

H1a—supported. Pre-service PE teachers rated AI's communicative and adaptive capabilities (PC1: 'Interprets human communication', M = 3.08; 'Improves on the basis of feedback', M = 3.15) more favourably than its autonomous decision-making capabilities (PC2: 'Always makes the right decision', M = 1.75; 'Always understands instructions accurately', M = 2.04), confirming the direction of attitudes hypothesised in H1a. H1b—descriptive support. Favorable AI attitudes were observed alongside moderate institutional satisfaction and reported knowledge barriers (27.6%) at the sample level, suggesting a receptivity–preparedness gap (H1b). Because individual-level co-occurrence was not directly tested, this should be regarded as a descriptive population-level pattern.

H2—supported. Part-time and master's-level students reported significantly greater interest in AI-related coursework ($p < 0.001$). As labour-market experience was not directly measured, the observed group difference cannot be attributed to professional contextualisation; the pattern is nonetheless consistent with the TAM framework of Alejandro et al. (2024), in which perceived usefulness—potentially reinforced by work experience—is the strongest predictor of AI adoption intentions.

H3—supported. Institutional AI satisfaction and interest were significantly positively associated ($\rho = 0.192$, $p < 0.01$). The quality of institutional experience is positively associated with student motivation, suggesting that institutional investment may be a relevant factor.

H4—no statistically significant gender differences were detected. In the PE teacher education context, no statistically significant gender differences were detected in AI attitudes or course interest; these findings do not establish gender equivalence but suggest that substantial gender differences were not evident in the outcomes examined.

5. Conclusions

Based on a sample of 416 Hungarian pre-service PE teachers, the present study provides empirical evidence that students are open and receptive to the pedagogical use of AI:

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sport performance analysis was rated as a relevant AI application by 73.3% of respondents; the communicative and adaptive capabilities of AI received high ratings on the attitude scale (M = 3.08–3.15); and only 7.7% expressed concern about career displacement. In parallel, knowledge gaps (27.6%), funding constraints (25.5%), and moderate satisfaction with institutional AI integration (M = 2.85, ±SD = 0.85) suggest that, as perceived by the students surveyed, institutional provision has not yet kept pace with student receptivity—a pattern that warrants further investigation through independent assessments of institutional readiness.

Part-time and master's-level students were significantly more open to AI-related coursework ($p < 0.001$), a pattern consistent with, though not directly attributable to, greater professional contextualisation among these student groups. Differences across institutions (EKKE: M = 3.36 vs. ELTE: M = 2.59) underline the substantive role of institutional context. The absence of significant gender differences suggests that, within PE, engagement with and use of digital technologies do not display a marked gender gap. These findings converge with those of Maberah et al. (2025), whose study of Jordanian PE students similarly documented positive AI attitudes alongside limited practical integration, reinforcing the cross-cultural generalisability of the receptivity–preparedness pattern.

The positive correlation between institutional satisfaction and interest ($\rho = 0.192$, $p < 0.01$) points to a weak positive association between institutional AI provision and student motivation.

Notwithstanding these limitations, the findings provide an empirical foundation for system-level AI integration in PE teacher education, including master's-level AI modules, the field integration of motion-analysis tools, and the dissemination of institutional good practices.

6. Limitations of the Study

A key strength of the present study is its broad institutional coverage, as data were collected from all Hungarian higher-education institutions offering physical education teacher education. Nevertheless, the findings should be interpreted in light of several limitations. The cross-sectional design does not allow for causal conclusions, and the use of self-reported questionnaire data may involve response bias. Although the sample provides substantial insight into the Hungarian context, the convenience-based recruitment procedure and national focus limit the generalisability of the findings to other educational systems. Future research should therefore employ longitudinal or mixed-method designs and include cross-national comparisons to examine how institutional AI readiness develops over time, building on emerging cross-national frameworks such as that of Le Xiu et al. (2026). A further theoretical limitation concerns the operationalisation of the SCT framework: while the study adopts a combined TAM-SCT perspective, direct measurement of self-efficacy beliefs was not included in the MIATT 2024_rev instrument, which constrains the full application of SCT predictions. A further limitation concerns response rate: the estimated overall response rate was 20.3% (N = 416 of a target population of 2054), with institution-level rates ranging from 6.9% to 46.9% (FIR/FIRSTAT data, Hungarian Educational Authority). Although these rates reflect the voluntary nature of participation and are within the range commonly observed in online academic surveys, differential non-response across institutions may have introduced systematic bias that cannot be fully quantified. Furthermore, the data do not include a direct measure of labour-market experience; consequently, the association between study format and AI-course interest cannot be directly attributed to professional contextualisation, and an adjusted analysis controlling for this variable was not feasible.

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Appendix A

Table A1. Rotated Component Matrix—AI Attitude Scale (N = 416).

Item	PC1	PC2	h^2
Can imitate human thinking	0.502	0.414	0.423
Can solve complex problems	0.524	0.435	0.464
Always makes the right decision	0.052	0.877	0.773
Surpasses human performance	0.636	0.136	0.423
Always understands instructions accurately	0.090	0.790	0.633
Improves on the basis of feedback	0.651	0.043	0.426
Interprets human communication	0.693	0.000	0.480
SS loadings	1.847	1.775	
% of variance	26.4%	25.4%	51.7%

Note. Principal component analysis with varimax rotation and Kaiser normalisation. Factor loadings $\geq$ 0.30 are considered substantive. PC1 = communicative–interpretive capabilities (α = 0.440, 3 items); PC2 = performance–developmental capabilities (α = 0.623, 4 items). Variance percentages reported in the main text (PC1: 35.4%, PC2: 16.3%, total: 51.7%, λ = 2.48 and 1.14 respectively) are pre-rotation eigenvalue-based; post-rotation SS loading-based values are shown in this table (PC1: 26.4%, PC2: 25.4%, total: 51.7%). h^2 = communality. KMO = 0.741; Bartlett's test: χ^2 = 446.26, df = 21, $p < 0.001$. Cronbach's α = 0.693. N = 416. The two-component solution is exploratory in nature; the item composition does not correspond perfectly to the a priori conceptual distinction underlying H1a (communicative/adaptive versus autonomous decision-making capabilities), and component-level findings should therefore be interpreted as exploratory empirical groupings rather than as confirmatory evidence of the hypothesised capability domains.

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