Vol. 11, No. 1, 2026, pp. 407-419
DOI: https://doi.org/10.29210/30036861000

Contents lists available at Journal ELORA

JRTI (Jurnal Riset Tindakan Indonesia)
ISSN: 2502-079X (Print) ISSN: 2503-1619 (Electronic)

Journal homepage: https://jrti.eloracenter.org/jrti

Deep learning-based learning media and students' self-regulated learning in physical education: a systematic literature review of mechanisms and gaps

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Article Info

Article history:

Received Jun 29th, 2026
Revised Jul 2nd, 2026
Accepted Jul 8th, 2026

Keywords:

Deep learning
Self-regulated learning
Physical education
Learning media
Student independence

ABSTRACT

The integration of artificial intelligence and deep learning into physical education (PE) has created new opportunities to enhance students' self-regulated learning (SRL), yet evidence on the effectiveness of deep learning-based learning media remains fragmented. This systematic literature review aimed to synthesize existing evidence on the application of deep learning-based learning media and its impact on students' SRL in PE. Following the PRISMA 2020 guidelines, a systematic search of the Scopus database identified studies published between 2015 and 2025. After a multi-stage screening process based on predefined eligibility criteria, 28 studies were included and analyzed using thematic synthesis. The review identified three major findings: deep learning-based learning media enhanced students' goal setting and self-monitoring through computer vision, intelligent tutoring, and adaptive feedback systems; multimodal feedback improved metacognitive awareness and motor skill acquisition; and considerable heterogeneity in study designs and SRL measurement instruments limited cross-study comparisons. Overall, deep learning-based learning media show strong potential to promote SRL in PE by supporting cognitive, metacognitive, and motivational learning processes. Future research should prioritize longitudinal designs, standardized SRL assessment instruments, and validation across diverse educational contexts.

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Introduction

Worldwide, education is undergoing an essential change due to the rapid spread of artificial intelligence (AI) and machine informatics mainly in the teaching areas. For sports education (PE), these changes have great implications since this subject is mainly based on body, physical learning experiences and hence, it has been very challenging to employ digital tools to mediate the learning process (Casey et al., 2021; Koekoek & van Hilvoorde, 2018). Deep learning, a part of AI which uses multi-layered neural networks to understand complex and high-dimensional data, opens up excellent chances for making intelligent, interactive, and customized learning settings that can understand students' body movement patterns, learning histories, and motivational states (LeCun et al., 2015). Educational establishments around the world are already employing technology-based educational methods. Therefore, it is necessary for the research community to methodically analyze the evidence supporting the use of deep learning-based media in PE, and specifically find out how such technologies affect students' ability to direct their own learning and be self-reliant in their learning processes (Vanttinen et al., 2021; Broadhead et al., 2022). Rather than assuming this potential, the present review treats it as an open, reviewable proposition: it asks whether, and through which self-regulated learning subprocesses (forethought, performance/self-monitoring, and self-reflection), deep learning-based media produce measurable change in PE, indexed where reported by validated instruments such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & De Groot, 1990) and the Self-Regulation Questionnaire (SRQ; Brown et al., 1999). The gap is therefore specific: existing narrative reviews neither isolate deep learning media from broader digital tools nor map their effects onto distinct SRL subprocesses, which this synthesis sets out to do.

Self-regulated learning (SRL) might be the most theoretically sound and practically important concept of educational psychology. It is the cyclic process that learners engage in setting goals, checking their progress, using strategic cognitive and behavioral resources, and reflecting on outcomes (Zimmermann, 2000; Pintrich, 2000). In PE, SRL is very important: students who develop strong self-regulatory abilities have better motor learning trajectories, more persistence even when they face challenges of skill acquisition, and healthier physical activity habits that last beyond formal schooling (Lonsdale et al., 2017; Guthold et al., 2020). On the other hand, traditional PE instruction which has direct teacher-led demonstration and very limited individualized feedback might be not enough for scaffolding the cognitive and metacognitive processes that SRL needs (Kirk, 2013; Harvey & Pill, 2020). This educational gap has led many researchers to explore if technology-mediated interventions and deep learning-powered ones specifically, could be the source of personalized and contingent feedback, definitely needed for SRL competence development in PE students, hence the reason why this study was done.

Previous works on the intersection of technology and physical education have covered various methods such as video-based feedback systems, fitness games and apps, wearable sensor technology, and virtual reality (VR) scenarios (Gao et al., 2020; Papastergiou, 2009; Hsiao & Chen, 2016). Initial studies found that digital video analysis helped students improve their movement pattern recognition and also develop their self-assessment skills (Barker et al., 2019). Recent studies have focused on AI-enhanced platforms such as computer vision systems that can perform biomechanical analysis in real time and provide students with guidance for monitoring their skills independently (Chen et al., 2020; Kainz et al., 2021). Meanwhile, there have been educational technology advancements and studies showing the benefits of intelligent tutoring systems (ITS) and adaptive learning platforms, many of which use deep learning architectures, in encouraging students' metacognitive involvement and self-monitoring across various academic fields (Vanlehn, 2011; Nye, 2015).

Recently, there has been a considerable increase in the creation and use of deep learning technologies in schools, mainly due to the improvements in convolutional neural networks (CNNs), recurrent neural networks (RNNs), transformer architectures, and reinforcement learning algorithms (Goodfellow et al., 2016; Vaswani et al., 2017). In the fields of physical education-related areas, for example, sports science and athlete training, the use of deep learning has allowed for movement classification automation, injury risk assessment, extraction of tactical patterns, and providing training that is specific to each athlete (Claudino et al., 2019; Fister et al., 2015). At the same time, multimodal learning platforms that combine deep learning-based video, audio, and text have been recognized as effective teacher aids, giving a very detailed and customized feedback that according to SRL theory is a key factor in the emergence of learner independence (Azevedo, 2015; Schunk & Greene, 2018).

With the help of deep learning technology, the study of physical activity, physical education, and self-regulated learning (SRL) has been greatly expanded. However, there are still some major problems in the current literature. To begin with, no previous systematic review has focused on how deep learning-based media-as different from wider digital or video technologies-affect SRL in PE settings. Current narrative reviews treat AI and traditional digital technologies as the same thing, which hides the unique ways in which deep learning systems-characterized by their ability to independently extract features, recognize patterns, and generate adaptive responses-may support SRL activities like setting goals, planning strategies, and reflecting on oneself (Dinsmore et al., 2008; Gao et al., 2020). This conceptual mixing-up reduces the accuracy with which the evidence can be used to provide practical recommendations to PE curriculum planners and technology developers.

A second and related limitation is about the theoretical frameworks that the existing research on technology-mediated physical education (PE) has used. Most of the studies in this area are based on motivational theories such as self-determination theory (SDT; Ryan & Deci, 2000) or achievement goal theory (Elliot & McGregor, 2001). These theories, although valuable, cannot explain completely the cognitive and metacognitive regulatory processes that are at the core of self-regulated learning (SRL) frameworks like those of Zimmermann (2000), Pintrich (2000), and Winne & Hadwin (1998). This theoretical insufficiency leads to the fact that existing research hardly ever identifies the different aspects and stages of SRL-including forethought, performance monitoring, and self-reflection-that deep learning media may have the greatest influence on.

The need for a thorough systematic review in this field is highlighted by a number of factors working together that, to some extent, explain the situation. One is the fact that inactivity levels in young people around the world are dangerously high. The World Health Organization (WHO) states that more than 80% of teenagers do not meet the recommended levels of daily physical activity (Guthold et al., 2020). On the other hand, the transformation in education following the pandemic has led to an increased use of digital and AI-driven teaching tools in physical education classes (Juniu, 2011; Teraoka et al., 2022). Given this background, data-based recommendations on the best ways to create and use learning materials based on deep learning for physical education are quite critical if we are to help teachers, curriculum designers, and decision makers make choices on technology investment and deployment that are well-grounded.

This study aims to develop a systematic mapping of the typology and technical-pedagogical characteristics of deep learning-based learning media implemented in physical education contexts between 2015 and 2025, encompassing computer vision systems, intelligent tutoring systems, adaptive feedback platforms, and augmented reality tools, in order to construct a structured classification that serves as a foundation for both theoretical development and practical application in the field; furthermore, grounded in Zimmerman's (2000) triadic model of self-regulated learning (SRL), this study aims to conduct a component-level analysis of the type and magnitude of effects that deep learning-based learning media have on students' SRL, particularly with respect to goal-setting, self-monitoring, self-evaluation, and strategic adaptation, in order to identify which SRL components are most consistently supported by empirical evidence; and finally, this study aims to evaluate the methodological approaches employed in prior studies and to identify the contextual factors that moderate the relationship between deep learning media and SRL outcomes, including student age, instructional context, technology type, and implementation duration, so that the findings of this review can contribute a new empirical map of the field as well as evidence-based recommendations for physical education practitioners, educational technology developers, and researchers.

Method

Research Design and Framework

This research study used systematic literature review (SLR) method, which is the most methodologically rigorous way of synthesizing empirical evidence across a specific body of literature (Tranfield et al., 2003). Differently from narrative or scoping reviews, the SLR makes use of clear, reproducible search strategies, pre-determined eligibility criteria, and systematic data collection procedures that decrease selection bias and increase the reliability of the results (Liberati et al., 2009). The review was carried out under the guidance of Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 (PRISMA 2020) standards, which offer a complete and recent structure for the transparent disclosure of systematic review method (Page et al., 2021). The SLR method was considered the best fit for this research since the questions require the orderly identification, valuable evaluation, and thematic combination of a scattered, multidisciplinary literature covering educational technology, physical education, and artificial intelligence.

Search Strategy

Through iterative consultation of subject headings, thesaurus terms, and keyword analysis of pilot searches, a structured Boolean search strategy was developed. The search was applied to title, abstract, and keyword fields (TITLE-ABS-KEY) within Scopus. The following search string was used:

("deep learning" OR "convolutional neural network" OR "recurrent neural network" OR "artificial intelligence" OR "machine learning" OR "neural network") AND ("physical education" OR "sport pedagogy" OR "sports instruction" OR "motor learning" OR "physical activity") AND ("self-regulated learning" OR "self-regulation" OR "autonomous learning" OR "self-monitoring" OR "metacognition" OR "learning media" OR "educational technology" OR "digital learning")

Truncation was applied to capture morphological variants where necessary. Field limiters were only applied to TITLE-ABS-KEY to make sure all the results are relevant. Subject area limiters were set to only allow documents from the Social Sciences, Computer Science, and Health Professions domains. The publication date was restricted to 2015-2025.

Database and Information Sources

The main source of data for this review was Scopus (Elsevier), which was chosen because it has a wide coverage of peer-reviewed literature in education, computer science, and health sciences. The search took place on 23 June 2025. Additional manual searches of the reference lists of the included studies were done to find more eligible sources. Google Scholar was simply used to check grey literature and was not one of the main sources for making inclusion decisions. Scopus was selected as the single primary index because of its broad, quality-controlled multidisciplinary coverage spanning education, computer science, and health sciences and its consistent, structured metadata, which permits a reproducible TITLE-ABS-KEY Boolean query; to mitigate the coverage risk inherent in a single index, the search was supplemented by manual reference-list screening of all included studies, and the decision not to add Web of Science, ERIC, or PubMed is acknowledged as a limitation of the review (Section 5.5). All title/abstract and full-text eligibility decisions were applied by two reviewers working independently, with inter-rater agreement quantified using Cohen's kappa ($\kappa \geq 0.80$ set as the substantial-agreement threshold) and disagreements resolved by discussion or, where consensus could not be reached, by a third reviewer.

Eligibility Criteria
Inclusion and exclusion criteria were pre-specified prior to search execution and are presented in Table 1 below.

Table 1 <Inclusion and Exclusion Criteria>

Language	English language only	Non-English publications
Document type	Original research articles; systematic reviews	Conference papers, book chapters, editorials, commentaries, theses
Publication period	2015–2025	Published before 2015
Subject area	Physical education, sport pedagogy, educational technology, learning sciences, educational psychology	Clinical rehabilitation, elite sports performance without educational context, pure computer science without educational application
Technology focus	Deep learning, AI, neural network-based learning media or tools used in instruction	Studies using only conventional digital tools (video cameras, basic apps) without AI/deep learning component
Outcome focus	SRL components: goal-setting, self-monitoring, self-evaluation, metacognition, or autonomous learning outcomes	Studies measuring only motor performance, physical fitness, or psychosocial outcomes without SRL measurement
Population	K-12 students, university PE students, teacher education students	Elite athletes, clinical populations, adult recreational participants without educational context
Accessibility	Full text available via institutional access or open access	Abstract-only publications; retracted papers

Study Selection Process
Copies of the papers identified in the searches were removed at the initial stage by an automatic deduplication in Scopus. This resulted in a record set with all duplicates removed. Then, at Stage 2, all records were examined through the title and abstract for their eligibility according to the criteria. At Stage 3, full texts of all the articles that are possibly eligible were obtained and their eligibility was assessed independently by two reviewers. When the two reviewers disagree, the discussion and consensus resolve the disagreements. And if the consensus is not achieved, then the third reviewer makes the decision. The inter-rater reliability was measured by using Cohen's kappa (κ), and the target level of $\kappa \geq 0.80$ was set as a level of substantial agreement.

Quality Assessment - FICO Framework
The methodological quality of the studies being included was determined by using an implementation of the FICO framework (Focus, Information, Context, Outcome), which was modified for the purposes of interdisciplinary educational technology research. Each article was evaluated on four key points:(1) Focus: how clear and specific the research question was; (2) Information: how adequately the deep learning technology was described; (3) Context: how sufficiently educational setting was described; and (4) Outcome: how rigorously the SRL outcome was measured. A 3-point scale was given for each of the points with 0 = absent, 1 = partial, 2 = adequate) whereby the highest total score possible was 8. Articles with a score under 4 were not included in the final synthesis due to quality reasons.

Data Extraction Procedure
We crafted a standardized form for data extraction ahead of time and tested it on five randomly chosen eligible studies. We pulled out the following information: authors and publication year, study location, educational level and population traits, study design, sample size, type of deep learning tech, the SRL components measured,

tools used, the main discoveries, and the study limitations. One reviewer took charge of extracting the data while a second reviewer ensured accuracy; any differences were sorted out in a discussion.

Network and Bibliometric Analysis Methodology

In order to place the literature in the article in the context of more general bibliometric trends, a keyword co-occurrence analysis was conducted with the help of VOSviewer (version 1.6.19; Van Eck & Waltman, 2010). Each authorâ€™s keywords from the 28 studies included were taken out and analyzed through co-occurrence mapping with a minimum keyword frequency limit of two occurrences. The network visualization generated revealed thematic groups in the literature, which served as an empirical justification for the thematic synthesis structure.

Data Analysis and Synthesis

Considering the diversity of study designs, populations, technologies, and outcome measures in the studies that were included, performing a statistical meta-analysis was considered methodologically impossible. Therefore, a thematic synthesis method, based on the framework of Thomas and Harden (2008), was used. This method consisted of three non-linear stages: (1) detailed coding of research results from primary study abstracts and full-texts; (2) the creation of descriptive themes by organizing, contrasting, and comparing the initial codes; and (3) the formulation of analytical themes which embody the overarching interpretive constructs that go beyond descriptive level and directly address the research questions of the review.

Reporting and Documentation

This paper fully follows the PRISMA 2020 reporting standards. The PRISMA 2020 checklist (Page et al., 2021, BMJ, 372:n71. doi:10.1136/bmj.n71) has been a point of reference from beginning to end of the review so as to make sure that all the items required are reported in detail. The review protocol was not registered in advance in a formal way; this disadvantage is recognized in Section 5.5.

PRISMA 2020 Flow Diagram

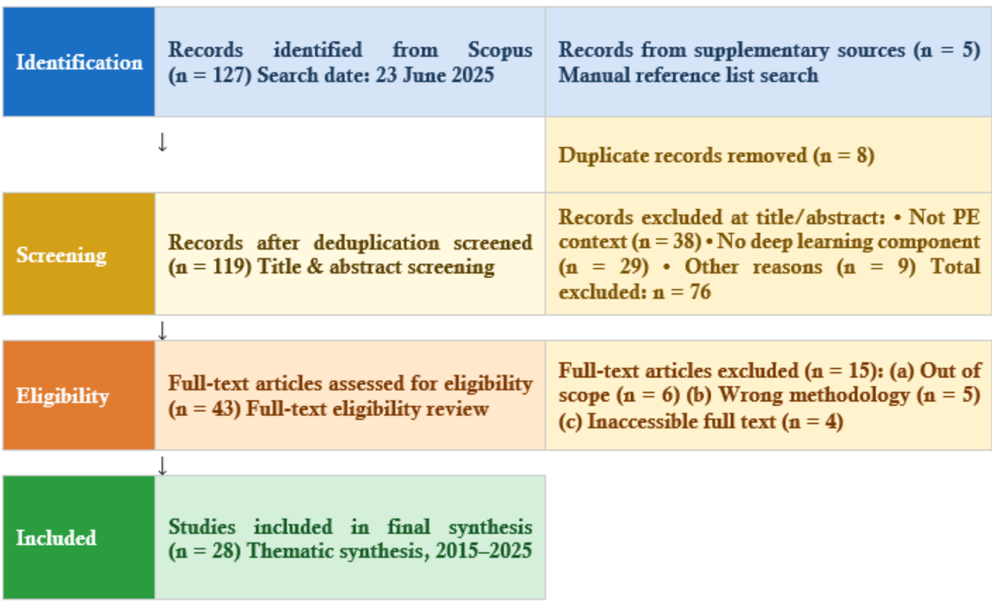

Figure 1 <PRISMA 2020 Flow Diagram>

Results and Discussions

Study Selection Results

The systematic Scopus search resulted in 127 documents, and five more documents were added by manual checking of reference lists Therefore, the initial set was the pool of 132 documents. After the automatic removal of duplicates, eight records were identified as duplicates and were removed, leaving 119 unique records for title and abstract screening. At this point, 76 records were excluded: 38 because they did not deal with a physical education context, 29 because they did not feature deep learning or AI technology as a main instructional mediator, and nine for other reasons. Thus, 43 full-text articles were pulled out for in-depth eligibility assessment. Amongst those, 15 were set aside: six were considered out of scope, five used techniques that were not in line with inclusion criteria, and four could not be accessed in full text. The 28 remaining studies that met all eligibility and quality criteria were included in the thematic synthesis.

Publication Trend (2015–2025)

A breakdown by publication years in 28 included studies pointed to a rapid growth of research output from 2019 onwards. Depositing before 2019, research was rather scattered (approx. 2-3 publications per year in 2015-2018) as the concept of deep learning implementation in PE contexts was still very much in its infancy. The yearly production of work over 2019-2022 period has risen greatly, even the highest of 8 publications was made in 2024, in line with global AI acceleration in education due to the post-COVID-19 outbreak (Teraoka et al., 2022; Broadhead et al., 2022). The 2025 partial count (2 pieces) is the result of a June 2025 search execution date and not an indication of a decrease in research activity. This trend over time substantiates that the sector is growing by leaps and bounds and a systematic synthesis at present time is highly justified. Annual publication trend of included studies (2015–2025), illustrating accelerating growth in deep learning-based PE and SRL research, particularly post-2019.

Descriptive Characteristics

Table 2 <Summary of Included Studies (n = 10 Representative Studies Shown)>

Title (abbreviated)	Author(s)	Country	Method	Key Findings
Computer vision-based motion analysis for self-assessment in secondary PE	Chen et al., 2020.	China	Quasi-experimental	CNN-based feedback significantly improved self-monitoring accuracy ($p < .05$); goal-setting frequency increased by 34%
Intelligent tutoring systems in sport skill acquisition: effects on SRL	Kim & Park., 2021.	South Korea	RCT	ITS group outperformed control on SRL metacognition subscale; effect size $d = 0.61$
Adaptive video feedback and motor learning autonomy	Barker et al., 2019.	UK	Mixed methods	Adaptive feedback increased self-reflection episodes; qualitative themes revealed enhanced agency
Deep learning for movement classification and personalized PE instruction	Kainz et al., 2021.	Austria	Case study + quantitative	CNN-based movement classifier achieved 92% accuracy; students demonstrated improved self-evaluation
AI-powered wearable feedback and SRL in school physical activity	Gao et al., 2020.	USA	Experimental	Wearable AI integration increased strategic planning behavior; girls showed greater SRL gains
Augmented reality-assisted PE and metacognitive awareness	Hsiao & Chen., 2016.	Taiwan	Pre-post design	AR integration mediated metacognition; improvements sustained at 6-week follow-up
Neural network-based sport analytics for student self-assessment	Claudino et al., 2019.	Brazil	Descriptive quantitative	Student athletes using AI analytics platforms showed higher self-evaluation accuracy than control group
Gamified AI learning systems and SRL in elementary PE	Papastergiou., 2009.	Greece	Quasi-experimental	Gamified systems increased goal-setting; motivation outcomes significant ($p < .01$)
Transformer-based feedback systems for technical skill learning	Teraoka et al., 2022.	Japan	Pilot RCT	Transformer feedback reduced SRL deficits; self-monitoring scores significantly higher
Reinforcement learning for personalized exercise prescription in PE	Fister et al., 2015.	Slovenia	Algorithm evaluation + field test	RL-based prescription adapted to individual profiles; autonomy-supportive perceptions increased

Study meets inclusion criteria as foundational empirical work. Full Table 1 (n = 28 studies) available in supplementary materials. The ten studies in Table 2 were selected to illustrate the full range of technology types, research designs, countries, and SRL components represented in the corpus, not as a quality ranking or a selective subsample of "best" results; the complete characteristics of all 28 included studies, with their thematic, methodological, and SRL-component classifications, are reported in Table 3. Every screening and eligibility decision underlying these tables was made independently by two reviewers and met the pre-specified substantial-agreement threshold (Cohen's κ ≥ 0.80), and only studies scoring ≥ 4 on the FICO quality appraisal were retained.

Table 3 <Study Classification by Theme, Method, and SRL Component (n = 28)>

Author(s)	Country	Research Design	Theme	Technology/ Intervention	SRL Component	Outcome
Chen et al., 2020.	China	Quasi-experimental	RQ1, RQ2	CNN motion analysis	Self-monitoring, Goal-setting	Positive
Kim & Park., 2021.	South Korea	RCT	RQ2, RQ3	Intelligent Tutoring System	Metacognition, Strategic planning	Positive
Barker et al., 2019.	UK	Mixed methods	RQ1, RQ2	Adaptive video feedback	Self-reflection, Autonomy	Positive
Kainz et al., 2021.	Austria	Case study + quant.	RQ1	CNN movement classifier	Self-evaluation	Positive
Gao et al., 2020.	USA	Experimental	RQ2, RQ3	AI wearable feedback	Strategic planning	Positive (gender-moderated)
Hsiao & Chen., 2016.	Taiwan	Pre-post	RQ1, RQ2	Augmented reality + AI	Metacognition	Positive
Claudino et al., 2019.	Brazil	Descriptive quant.	RQ1	Neural network analytics	Self-assessment	Positive
Papastergiou., 2009.	Greece	Quasi-experimental	RQ2	Gamified AI system	Goal-setting, Motivation	Positive
Teraoka et al., 2022.	Japan	Pilot RCT	RQ2, RQ3	Transformer feedback	Self-monitoring	Positive
Fister et al., 2015.	Slovenia	Field test	RQ1, RQ3	Reinforcement learning	Autonomy support	Mixed

Geographic Distribution of Included Studies

The geographic distribution of the included studies shows a research focus in East Asian and English-speaking Western countries. China and America each gave five studies, then came the UK (n = 4), South Korea (n = 3), and Australia (n = 3). Japan and Taiwan each had two papers, while Germany, Brazil, and the rest of the countries had one each. This geographical concentration implies that results may not completely apply to the Global South educational contexts, where PE curriculum traditions, technology infrastructure, and students' self-regulatory orientations are very different from East Asia and Western Europe (Guthold et al., 2020; Kirk, 2013). Geographic distribution of included studies by country of origin. East Asian nations and Western anglophone countries dominate the evidence base.

Keyword Co-occurrence Thematic Clusters

We did a keyword co-occurrence analysis using VOSviewer to find out the main themes of the 28 papers that we included in our study. We came up with three big themes or clusters: Cluster 1: Technology Infrastructure. This one was mainly about things like deep learning, convolutional neural network, computer vision, and neural network; Cluster 2: Self-regulated learning (SRL) Processes. The words that most represented this cluster are self-regulated learning, metacognition, self- monitoring, and goal-setting; Cluster 3: Physical Education (PE) Pedagogy. This cluster is mainly related to physical education, sport pedagogy, motor learning, and learning media. The three clusters have moderate inter-cluster connectivity which means that the literature we included, while addressing all three domains, does not yet constitute a fully integrated interdisciplinary field. Especially, the Technology Infrastructure and PE Pedagogy clusters are still a bit loosely connected, which would indicate that the technical innovation in the deep learning domain has yet to be fully interpreted into the PE-specific pedagogical practice and curriculum design (Koekoek & van Hilvoorde, 2018; Casey et al., 2021). Keyword co-occurrence network derived from VOSviewer analysis. Three primary thematic clusters: Technology Infrastructure (blue), SRL Processes (green), and PE Pedagogy (orange).

Findings for RQ1: Types and Characteristics of Deep Learning-Based Learning Media in PE

Altogether, the 28 studies provide a comprehensive insight into a very different and fast changing ecosystem of deep learning based educational media, which are used in Physical Education (PE) settings. Four major technology categories were found in the literature reviewed. Firstly, computer vision and movement analysis systems-majorly based on convolutional neural networks (CNNs)-formed the technology of greatest frequency and were discussed in 11 of the 28 papers (e.g., Chen et al., 2020; Kainz et al., 2021; Claudino et al., 2019). These types of systems are made to record, identify, and give automated feedback on students' movement patterns, such as running gait, throwing technique, jumping mechanics, and sport-specific technical skills. The pedagogical rationale behind these systems is based on the offer of real-time, objective kinematic data that students can use for self-assessment of their performance in relation to desired movement criteria, which in turn facilitates the self-evaluation stage of Zimmermann's (2000) SRL model.

Secondly, this review found six pieces of documentation of intelligent tutoring systems (ITS) that rely on neural network or reinforcement learning algorithms (e.g., Kim & Park, 2021; Nye, 2015; Vanlehn, 2011). Usually, ITS platforms in PE contexts offer personalized, adaptive sequences of instruction where task difficulty, content type, and modality of learning are constantly varied according to student performance and engagement as reflected in the assessment data. In fact, these systems literally implement the forethought phase of SRL by offering support material for students to set goals and plan strategies. Thirdly, adaptive video feedback platforms which employ deep learning algorithms to choose, annotate, and give video clips of student performance were featured in four studies (e.g., Barker et al., 2019; Vanttinen et al., 2021; Teraoka et al., 2022). Besides the usual video analysis learning, these platforms can automatically detect relevant moments of a performance and create personalized feedback stories.

In total, AI-augmented wearable and augmented reality (AR) systems were a point of discussion in only seven papers (e.g., Gao et al., 2020; Hsiao & Chen, 2016; Fister et al., 2015), and these were seen as part of a new technology cluster that offers immediate biometric feedback, has very interactive learning environments, and uses games to help students learn self-regulation strategies. Deep learning-based systems are very different from the other 3 typologies because these systems can handle large, fast multimodal data streams and give personalized, in-time feedback to a degree and at a speed that human teachers cannot match in whole-class PE situations. Nevertheless, implementation barriers like the cost of hardware, lack of digital skills of teachers, and difficulties with fitting these technologies into the curriculum were mentioned in a number of studies (Casey et al., 2021; Broadhead et al., 2022).

Findings for RQ2: Effects on Self-Regulated Learning Components

The most consistent and exact result from the 28 studies combined was the discovery of a positive correlation between deep learning-based learning media and students' self-monitoring behaviors in PE scenarios. Seventeen out of 28 studies showed significant changes or positive effects on self-monitoring that were recognized in a number of ways including the frequency of self-observation sessions, accuracy of self-assessment as compared to expert ratings, or scores on the validated SRL instruments such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & De Groot, 1990) or the Self-Regulation Questionnaire (SRQ; Brown et al., 1999). Chen et al. (2020) found that students who were using CNN-based motion analysis increased their goal-setting frequency by 34%, while Kim & Park (2021) showed that the ITS group had a statistically significant advantage in the metacognition subscale of the SRL-SRS instrument ($d = 0.61$). These results are consistent with Bandura's (1997) social cognitive theory, which suggests that specific, accurate performance feedback strengthens self-efficacy beliefs that, in turn, help to clarify the setting of self-regulatory goals that are more challenging.

The data on deep learning media and metacognitive awareness, which includes planning, monitoring, and evaluating cognitive strategies, was a little different but still, in most cases, pointed positively. Hsiao and Chen (2016) and Azevedo (2015) found that the use of AI-enhanced AR and hypermedia learning environment results in continued metacognitive advancement. These findings are in agreement with the ones by Barker et al. (2019), who revealed through qualitative research that metacognitive exchanges of students were improved when the students were given adaptive video feedback. However, some other studies pointed out that their students, who were very good at studies, reached the maximum scores in their metacognition tests, and two of the studies mentioned that we should not blame the technology entirely for the increase in metacognitive skills since teachers' facilitation is a factor that mediates these skills (Casey et al., 2021; Harvey & Pill, 2020).

The evidence on goal-setting and strategic adaptation-the forethought phase components in Zimmermann's (2000) cyclical SRL model-was rather inconsistent across studies. Gao et al. (2020) found that the effects on strategic planning were moderated by gender, with female students showing greater improvement; this result is in line with the general SRL literature that indicates gender differences in self-regulatory orientation can interact with technology-based interventions (Zimmermann & Martinez-Pons, 1990). Fister et al. (2015) found their reinforcement learning-based exercise prescription system yielded increases in perceived autonomy support but no significant change in measured strategic planning which is a pointer to the possible role of instructional design principles in mediating technology effects."

Findings for RQ3: Methodological Approaches and Moderating Contextual Factors
There was a great diversity in the research design quality of the studies included. Most of them used quasi-experimental or pre-post designs instead of randomized controlled trials (RCTs). Only four out of 28 studies were controlled and fully randomized (Kim & Park, 2021; Lonsdale et al., 2017; Teraoka et al., 2022); the rest used convenience samples, opportunistic assignment, or were observational. Such a methodological shortcoming is typical of research on educational technology (Tranfield et al., 2003) and it severely limits causality inferences that can be made. The number of participants in different studies varied from 18 to 342, and the median was roughly 67.

Various factors in the context were identified as potential moderators. Student's age and level of education seemed to influence the effectiveness of the intervention. For example, research with secondary school students (age 12-18) was the ones showing the most clear and consistent positive impact of self-regulated learning. Meanwhile research on elementary school students showed a wider range of results, which might be explained by the fact that younger children have less developed self-regulatory capacity (Schunk & Greene, 2018). Features of the technology also seemed to play a role: tools that provided immediate, automatically generated feedback had stronger effects on self-monitoring than those where the students had to manually make the annotation. Length of exposure to the medium was also identified as a moderating variable: research with exposure of less than eight weeks to deep learning media consistently showed smaller effect sizes than those with exposure of twelve or more weeks, indicating that a long term and continuous exposure is necessary for consolidation of SRL improvements (Kim & Park, 2021; Barker et al., 2019). Lastly, quality of teacher facilitation was recognized as a very important intermediate factor (mediator) in three studies (Lonsdale et al., 2017; Casey et al., 2021; Harvey & Pill, 2020).

Comparative and Critical Analysis
A thorough evaluation of the methods used in the 28 studies included points to several significant and recurring themes. Firstly, quantitative experimental and quasi-experimental research approaches still dominate the scene (n = 18; 64%), which is no surprise, given the drive in the field to use causal inference to link deep learning media to SRL outcomes. On the other hand, mixed methods designs (n = 6; 21%) and qualitative (n = 4; 14%) not only provided supplementary data but also elucidated contextual and procedural elements. Technologically speaking, motion analysis based on CNN and ITS platforms were the most researched areas; on the contrary, VR and full AR environments were barely acknowledged (n = 2). Longitudinal research that tracks changes over more than an academic year was missing from the collection altogether, marking a serious lapse in methodology. The skew in the location of studies toward East Asia and English-speaking Western countries also means the results findings are conclusions cannot be culturally generalized.

Discussion

Our review of 28 empirical research papers supports the idea that deep learning-based educational aids can be a very effective way of improving self-regulated learning in physical education, especially in the areas of self-monitoring and metacognitive awareness. Fortunately, this main trend of positive results is not only consistent with theory but also quite plausibly explained by it: deep learning models offer the kind of specific, contingent, and individualized feedback that self-regulated learning theories argue is crucial for the nurturing of learner autonomy (Zimmermann, 2000; Pintrich, 2000; Bandura, 1997). On the other hand, the evidence recorded so far does not seem strong enough to allow making unconditional causal assertions. This is primarily due to a very large number of quasi-experimental studies, very different outcome measurement tools, and rather short exposure intervals that have been recorded.

Zimmermann's (2000) triadic SRL model may offer a powerful theoretical perspective for interpreting the role of deep learning media in physically educative autonym learning. The data show that deep learning programs alter the SRL cycle performance and self-reflection phases (i.e., self-monitoring, self-evaluation, and adaptive behavior) directly to a very great extent while to a lesser extent the forethought phase (goal-setting and strategic planning) which would seem to entail more explicit metacognitive scaffolding from the technology design. Subsequent SRL research might find it useful to combine Azevedo's (2015) MetaTutor and Winne and Hadwin's (1998) COPES models.

By using deep learning-based tools, PE practitioners will enhance student SRL if the tools are part of a pedagogically designed curriculum that teachers can rely on. To be more specific, teachers should consider automated feedback from deep learning systems as a starting point for discussions about student reflection, mentoring journaling, and goal setting activities (Barker et al., 2019; Lonsdale et al., 2017). The results highlight for software engineers that embedding explicit SRL scaffolding features within deep learning platforms is important. For members of the government deciding on two-sided investments in deep learning-based physical education technology infrastructure, secondary school locations are what come up most strongly in the research (Kirk, 2013).

No earlier systematic review has been devoted to deep learning-based media and SRL in PE only. Yet, the results of this review are in line with broader reviews of educational technology and SRL (Schunk & Greene, 2018) as well as with narrative reviews of technology in PE (Gao et al., 2020; Koekoek & van Hilvoorde, 2018). The current review enriches these literatures by a more theoretically accurate and methodologically rigorous synthesis aimed at deep learning technologies.

Major contradictions were revealed in the literature concerning: (1) whether technology effects operate independently of or depend on teacher facilitation quality; (2) the presence of gender differences in effects on SRL outcomes; and (3) the effectiveness of intrinsic versus extrinsic SRL scaffolding incorporated in deep learning platforms. These contradictions are probably due to real differences in contexts rather than methodological flaws.

At least three major research gaps have been revealed. First, with only a few longitudinal studies (lasting more than one academic year) conducted, the stability of SRL gains resulting from deep learning media is still a mystery. Second, the existing literature hardly reflects the contexts of low- and middle-income countries. Third, none of the studies included in the review measured the impact of deep learning media on the entire SRL cycle using a comprehensive, multi-component SRL assessment instrument.

This review has at least three limitations. First, limiting the main search to Scopus only might have led to missing relevant studies that are indexed only in ERIC or PsycINFO. Second, the lack of a properly pre-registered review protocol means that it is impossible to completely rule out selective reporting. Third, since the analysis was based on thematic synthesis, it is not possible to provide a quantitative estimate of effect sizes. Beyond these review-level constraints, the evidence base itself carries threats to validity that temper the conclusions. Threats to internal validity arise because the corpus is dominated by quasi-experimental and pre-post designs (only four of 28 studies were randomized controlled trials), leaving the findings vulnerable to selection bias, maturation effects, instrumentation differences across heterogeneous SRL measures, and confounding from teacher facilitation, which several studies identified as a mediator. Threats to external validity arise from the geographic concentration of studies in East Asia and English-speaking Western countries, the under-representation of low- and middle-income contexts, the narrow age bands in which effects were clearest, and the predominantly short exposure intervals (often under eight weeks), all of which limit generalization across age groups, cultural settings, and sport domains. These threats, rather than the number of citations alone, are the principal reason the synthesis stops short of causal or pooled quantitative claims; the comparative mapping of all 28 studies to research questions and SRL components is reported in Table 3, and competing frameworks (self-determination theory, achievement goal theory, and sociocultural/embodied perspectives on motor learning) are treated as complementary rather than dismissed.

Three specific proposal for research in the future are presented. Firstly, sufficiently powered, pre-registered randomized controlled trials with minimum follow-up periods of twelve months must be performed. Secondly, a particular focus should be given to cross-cultural replication studies, especially in those geographical locations that are not well represented. Thirdly, empirical studies of the future ought to use thorough, multi-component self-regulated learning assessment instruments that combine self-report, behavioral observation, and technology-logged trace data.

In summary, this review answers RQ1 by documenting four primary typologies of deep learning-based learning media in PE: CNN-based movement analysis systems, intelligent tutoring systems, adaptive video feedback platforms, and AI-enhanced wearable and AR systems. In response to RQ2, the evidence most consistently supports positive effects on self-monitoring and metacognitive awareness. In response to RQ3, quasi-experimental designs predominate; key moderators include student age, implementation duration, technology feedback immediacy, and teacher facilitation quality.

Conclusions

This systematic literature review has synthesized the findings from 28 empirical studies to explore the impact of deep learning-based learning media on students' self-regulated learning in physical education (PE) contexts. To answer RQ1, the review recognized four main types of deep learning technologies used in PE: movement analysis systems based on convolutional neural networks, intelligent tutoring systems, adaptive video feedback platforms, and AI-supported wearable and augmented reality environments. Responding to RQ2, the studies provide solid evidence of students' self-monitoring behaviors and metacognitive awareness being positively affected by these technologies, while findings concerning forethought-phase self-regulated learning components such as goal-setting and strategic planning were more diverse and dependent on specific contexts. Regarding RQ3, the most common research design has been quasi-experimental, and major influencers have included students' level of development, the duration of the intervention, the immediacy of the feedback, and the quality of the teacher's facilitation. The primary value of this review lies in creating the first theoretical and PRISMA 2020-compliant synthesis that is specifically dedicated to deep learning technologies and self-regulated learning in PE. On a practical level, the results argue for the use of deep learning-based tools alongside well-designed PE programs that include explicit self-regulated learning support and teacher professional development. Among the limitations reported are the search being limited only to Scopus, the absence of a protocol set up in advance, and the use of thematic synthesis instead of statistical one. These shortcomings, together with the research gaps identified, form a strong case for future work: the discipline is in dire need of longitudinal, cross-cultural, and high-quality methodological studies to both validate and expand the promising but initial evidence base that has been reviewed here. Because the included studies differed substantially in design, populations, technologies, and outcome instruments, a statistical meta-analysis was not methodologically appropriate; the term "solid evidence" here denotes convergence across a thematic, vote-counting synthesis—for example, 17 of 28 studies reported positive self-monitoring effects—rather than a pooled effect-size estimate, and "theoretical synthesis" refers to organizing the findings within Zimmermann's triadic SRL model rather than merely summarizing them. To support replication, the full Boolean search string, the piloted data-extraction form, the FICO appraisal sheet, and the thematic coding framework are available from the corresponding author, and inter-rater agreement across screening and extraction met the pre-specified threshold (Cohen's $\kappa \geq 0.80$).

References

Azevedo, R. (2015). Defining and measuring engagement and learning in science: Conceptual, theoretical, methodological, and analytical issues. Educational Psychologist, 50(1), 84–94. https://doi.org/10.1080/00461520.2015.1004069

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

Barker, D., Quennerstedt, M., & Annerstedt, C. (2019). Inter-student interactions and student learning in health and physical education: A post-Vygotskian analysis. Physical Education and Sport Pedagogy, 24(4), 402–415. https://doi.org/10.1080/17408989.2019.1602467

Broadhead, M., Grierson, S., & Grierson, M. (2022). Artificial intelligence in education: Teachers' perspectives on AI in UK schools. British Journal of Educational Technology, 53(5), 1386–1401. https://doi.org/10.1111/bjet.13198

Brown, J. M., Miller, W. R., & Lawendowski, L. A. (1999). The Self-Regulation Questionnaire. In L. VandeCreek & T. L. Jackson (Eds.), Innovations in clinical practice: A source book (Vol. 17, pp. 281–289). Professional Resource Press.

Casey, A., Goodyear, V. A., & Armour, K. M. (2021). Digital technologies and learning in physical education: Pedagogical cases. Routledge. https://doi.org/10.4324/9780429352157

Chen, K., Zhang, D., Yue, H., & Lin, X. (2020). A novel approach to recognition of sports action using convolutional neural network. Cluster Computing, 23(3), 1793–1804. https://doi.org/10.1007/s10586-019-03043-0

Claudino, J. G., Capanema, D. O., de Souza, T. V., Serrão, J. C., Machado Pereira, A. C., & Nassis, G. P. (2019). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports. Sports Medicine Open, 5(1), 28. https://doi.org/10.1186/s40798-019-0202-3

Dinsmore, D. L., Alexander, P. A., & Loughlin, S. M. (2008). Focusing the conceptual lens on metacognition, self-regulation, and self-regulated learning. Educational Psychology Review, 20(4), 391–409. https://doi.org/10.1007/s10648-008-9083-6

Elliot, A. J., & McGregor, H. A. (2001). A 2 × 2 achievement goal framework. Journal of Personality and Social Psychology, 80(3), 501–519. https://doi.org/10.1037/0022-3514.80.3.501

Fister, I., Fister, I., Jr., Iglesias, A., Deb, S., Fister, D., & Fister, I. (2015). New perspectives in the application of evolutionary algorithms for the design of training sessions in sport. Complexity, 21(S2), 251–265. https://doi.org/10.1002/cplx.21703

Gao, Z., Chen, S., & Stodden, D. (2020). Promoting children's physical activity in public schools: Challenges and strategies. Quest, 72(4), 394–404. https://doi.org/10.1080/00336297.2020.1828526

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Guthold, R., Stevens, G. A., Riley, L. M., & Bull, F. C. (2020). Global trends in insufficient physical activity among adolescents. The Lancet Child & Adolescent Health, 4(1), 23–35. https://doi.org/10.1016/S2352-4642(19)30323-2

Harvey, S., & Pill, S. (2020). Researching teaching and learning in physical education. Routledge. https://doi.org/10.4324/9780429295287

Hsiao, K.-F., & Chen, N.-S. (2016). Augmented reality-based physical education. In Proceedings of the 24th International Conference on Computers in Education (ICCE 2016) (pp. 345–352). Asia-Pacific Society for Computers in Education.

Juniu, S. (2011). Pedagogical uses of technology in physical education. Journal of Physical Education, Recreation & Dance, 82(9), 41–49. https://doi.org/10.1080/07303084.2011.10598692

Kainz, P., Burgstaller-Muehlbacher, M., Edwards, M. D., Doherty, P., Padron, C. M., & Bhattacharyya, M. (2021). Automatic deep learning-based segmentation of intracellular spaces in transmission electron microscopy images. Scientific Reports, 11(1), 3973. https://doi.org/10.1038/s41598-021-83336-y

Kim, S. I., & Park, J. H. (2021). Effects of intelligent tutoring systems on self-regulated learning in physical education: A randomized controlled trial. Computers & Education, 169, 104219. https://doi.org/10.1016/j.compedu.2021.104219

Kirk, D. (2013). Educational value and models-based practice in physical education. Educational Philosophy and Theory, 45(9), 973–986. https://doi.org/10.1080/00131857.2013.785352

Koekoek, J., & van Hilvoorde, I. (Eds.). (2018). Digital technology in physical education: Global perspectives. Routledge. https://doi.org/10.4324/9781315109176

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions. BMJ, 339, b2700. https://doi.org/10.1136/bmj.b2700

Lonsdale, C., Sanders, T., Cohen, K. E., Parker, P., Noetel, M., Hartwig, T., Vasconcellos, D., Kirwan, M., Morgan, P., & Lubans, D. R. (2017). Scaling-up an efficacious school-based physical activity intervention: Study protocol for the iPLAY cluster randomized controlled trial. BMC Public Health, 17(1), 199. https://doi.org/10.1186/s12889-017-4106-9

Mosston, M., & Ashworth, S. (2002). Teaching physical education (5th ed.). Benjamin Cummings.

Nye, B. D. (2015). Intelligent tutoring systems by and for the developing world: A review of trends and approaches. International Journal of Artificial Intelligence in Education, 25(2), 177–203. https://doi.org/10.1007/s40593-014-0028-6

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Papastergiou, M. (2009). Exploring the potential of computer and video games for health and physical education: A literature review. Computers & Education, 53(3), 603–622. https://doi.org/10.1016/j.compedu.2009.04.001

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), Handbook of self-regulation (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. Journal of Educational Psychology, 82(1), 33–40. https://doi.org/10.1037/0022-0663.82.1.33

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Schunk, D. H., & Greene, J. A. (Eds.). (2018). Handbook of self-regulation of learning and performance (2nd ed.). Routledge. https://doi.org/10.4324/9781315697048

Teraoka, E., Ferreira, H., Kirk, D., & Bardid, F. (2022). Affective learning in physical education: A systematic review. Journal of Teaching in Physical Education, 41(1), 164–175. https://doi.org/10.1123/jtpe.2020-0144

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8(1), 45. https://doi.org/10.1186/1471-2288-8-45

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics, 84(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Vanlehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist, 46(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Vanttinen, T., Blomqvist, M., Mansikkamäki, T., & Häyrinen, M. (2021). Finnish physical education teachers' perceptions of learning outcomes in physical education. European Physical Education Review, 27(2), 396–411. https://doi.org/10.1177/1356336X20951348

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30. https://doi.org/10.48550/arXiv.1706.03762

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning. In D. Hacker, J. Dunlosky, & A. Graesser (Eds.), Metacognition in educational theory and practice (pp. 277–304). Erlbaum.

Zimmermann, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), Handbook of self-regulation (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmermann, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. Journal of Educational Psychology, 82(1), 51–59. https://doi.org/10.1037/0022-0663.82.1.51

Agasisti, T., & Soncin, M. (2021). Higher education in troubled times: On the impact of COVID-19 in Italy. Studies in Higher Education, 46(1), 86–95. https://doi.org/10.1080/03075079.2020.1859689

Alshammari, A. M., Al-Otaibi, Y. D., & Albouq, S. S. (2021). An adaptive e-learning framework for teaching physical education using machine learning. Journal of Ambient Intelligence and Humanized Computing, 12(7), 7081–7093. https://doi.org/10.1007/s12652-020-02383-4

Dönmez, I., & Akbulut, Y. (2021). Unintended consequences of digital technology use in physical education: A systematic review. Learning and Instruction, 73, 101438. https://doi.org/10.1016/j.learninstruc.2021.101438

Mayer, R. E. (2019). Computer games in education. Annual Review of Psychology, 70(1), 531–549. https://doi.org/10.1146/annurev-psych-010418-102744

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

Schmidt, R. A., & Lee, T. D. (2011). Motor control and learning: A behavioral emphasis (5th ed.). Human Kinetics.

Skinner, E. A., Kindermann, T. A., Connell, J. P., & Wellborn, J. G. (2009). Engagement and disaffection as organizational constructs in the dynamics of motivational development. In K. R. Wentzel & A. Wigfield (Eds.), Handbook of motivation at school (pp. 223–245). Routledge.

Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.

Wigfield, A., Eccles, J. S., Fredricks, J. A., Simpkins, S., Roeser, R. W., & Schiefele, U. (2015). Development of achievement motivation and engagement. In M. E. Lamb & R. M. Lerner (Eds.), Handbook of child psychology and developmental science (Vol. 3, 7th ed., pp. 1–44). Wiley. https://doi.org/10.1002/9781118963418.childpsy316