

Brain-Based Online Learning Design in Blended Physical Education: Effects on Basketball Skill Acquisition, Physical Fitness, and Learning Motivation

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Abstract

This study examined the effects of brain-based online learning design within a blended basketball learning environment on basketball technical skills, physical fitness, and learning motivation among university students. A quantitative pretest–posttest controlled experimental design was employed with 100 second-year undergraduate students assigned to an experimental group (n = 50) and a control group (n = 50). Over a 12-week intervention, both groups received identical basketball content and face-to-face instruction, while the online component differed in design. The experimental group engaged with online modules structured through the B.R.A.I.N.-B.A.S.E.D. framework, incorporating multimodal visualisation, structured repetition, active learning, emotional engagement, and interactive discussion. The control group received conventional online instruction. Results showed that the experimental group significantly outperformed the control group in basketball technical skills and learning motivation, with large effect sizes across overall technical performance and all motivation dimensions. In contrast, no significant between-group difference was found for physical fitness, although both groups improved over time. These findings suggest that brain-based online learning design is particularly effective for enhancing cognitive performance and affective outcomes in blended physical education, but has limited influence on physiological outcomes. The study contributes to educational computing research by demonstrating how theory-driven online instructional design can support embodied learning in higher education physical education.

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Introduction

Technology-enhanced learning (TEL) is best understood not as the simple addition of digital tools to teaching, but as the design of environments in which technologies, tasks, representations and interactions are organised to support learning. This distinction is longstanding. Clark (1983) cautioned against attributing learning gains to media alone, whereas Kozma (1994) argued that media matter when their affordances are aligned with cognitive processes and instructional methods. More recently, a learning sciences perspective has sharpened this argument by positioning TEL as a theory-informed design problem in which the value of technology depends on how it supports knowledge construction, participation, feedback and transfer across contexts (Kyza, 2023).

Blended learning, which integrates online and face-to-face instruction, has become a widely adopted approach in higher education due to its flexibility and potential to enhance engagement and learning outcomes (De Bruijn-Smolters & Prinsen, 2024; Garrison & Kanuka, 2004; Graham, 2006). However, evidence suggests that blended learning is not inherently effective. Blended learning is therefore most defensible when it purposefully integrates face-to-face instruction with online experiences that extend access, reflection and interaction, rather than simply digitising conventional delivery (Garrison & Kanuka, 2004; Graham, 2006; Choi-Lundberg et al., 2023). Its success depends on how well the online and offline components are designed and aligned (Wang et al., 2022). This design issue is particularly relevant in physical education, where learning involves both cognitive understanding and embodied skill execution (Forte et al., 2023; Wang et al., 2022). Basketball, as a representative sport, requires the integration of technical knowledge, motor coordination, cognitive processes, physical capacities and decision-making (Gou & Li, 2023; Senger, 2026).

Traditional teaching approaches in basketball often rely on demonstration and repetitive drills (Krause et al., 2008; Krause & Nelson, 2019), which may not adequately support cognitive engagement or individual learning differences. Brain-based learning provides a theoretical foundation for addressing these limitations. It emphasizes alignment between instructional strategies and cognitive processes such as attention, memory, and emotional engagement (Caine & Caine, 1991; Jensen, 2005). Empirical evidence suggests that brain-based learning can enhance motivation and learning outcomes (Akyürek & Afacan, 2013a; Akyürek & Afacan, 2013b; Amjad & Tabbasam, 2024; Uzezi & Jonah, 2017). However, its application within digital learning environments, particularly in physical education contexts where learning is both cognitive and embodied, remains relatively underexplored. Within this context, a brain-based online framework such as B.R.A.I.N.-B.A.S.E.D. (Hileman, 2006) is best framed as a neuroscience-informed instructional heuristic rather than as a literal translation of laboratory neuroscience into pedagogy. Early brain-compatible education literature emphasised patterning, emotion, context and active engagement (Caine & Caine, 1991; Jensen, 2005), but contemporary justification is stronger when linked to current evidence on multisensory learning and motor plasticity. Coordinated visual and verbal representations can improve learning when they support cross-modal integration and reduce ambiguity in how learners encode information (Mayer, 2020; Shams & Seitz, 2008; Stein & Stanford, 2008). At the motor level, repeated and progressively varied practice supports experience-dependent neuroplasticity, strengthening and stabilising neural circuits involved in motor control; transfer is more likely when practice also requires attention, correction and adaptation rather than rote repetition alone (Dayan & Cohen, 2011; Ericsson et al., 1993).

For online basketball instruction, this means that slow-motion demonstrations, multi-angle visualisation, segmentation of movement phases, and structured opportunities for rehearsal and feedback are theoretically defensible not because they are “brain-based” in a loose sense, but because they align with evidence on multimodal encoding and skill learning.

This study addressed the aforementioned gap by examining the implementation of brain-based learning design within the online component of a blended learning framework. Specifically, it investigated the effects of brain-based online learning in a blended implementation on three critical domains: basketball technical skill acquisition, physical fitness, and learning motivation. Building on this focus, the study adopted a design-oriented perspective by conceptualizing the online component not merely as a delivery medium, but as a learning environment shaped by theory-driven design principles for basketball learning. In doing so, it seeks to understand how design features grounded in neuro-pedagogy can affect cognitive processing, perceptual-motor integration, and learner motivation in basketball. In the context of basketball, skill execution is a multifaceted process requiring the seamless coordination of technical knowledge, visual perception, and motor control. The design-centric approach of this study evaluates how brain-based learning principles were operationalized into cohesive digital architecture that synchronizes cognitive processing, multi-sensory visualization, and social-emotional engagement to optimize the acquisition and internalization of this complex, multifaceted process.

Conceptual Framework

Figure 1 illustrates the conceptual framework guiding this study. The framework positions blended learning as the overarching instructional architecture, combining face-to-face and online learning components. The face-to-face component focuses on physical practice, feedback, and skill execution in basketball, while the online component serves as a cognitively and affectively supportive learning environment that prepares and reinforces skill acquisition. Both the experimental and control groups receive identical face-to-face basketball instruction.

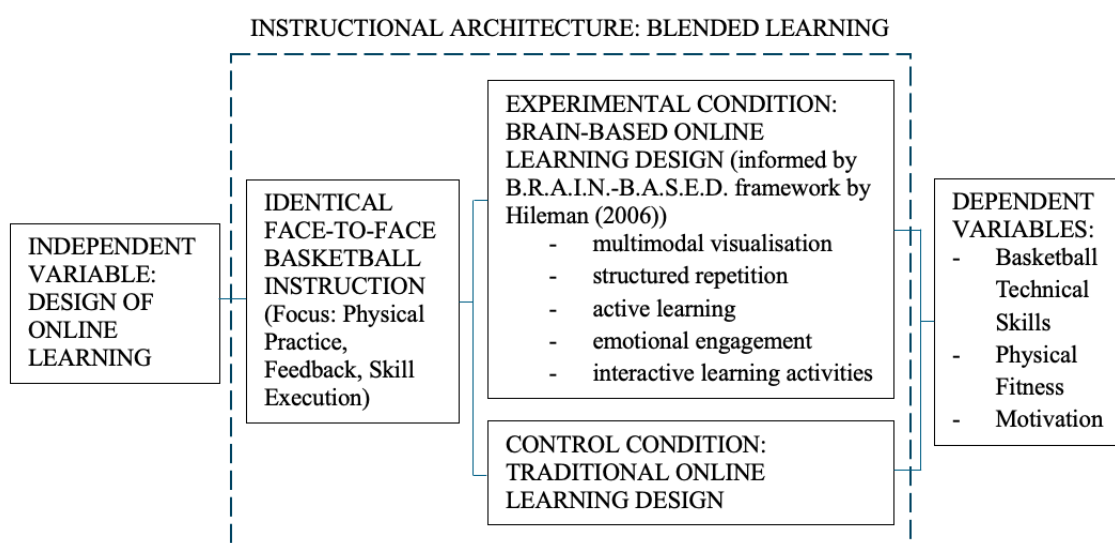


Figure 1. Conceptual Framework

The core independent variable in this study is the design of the online learning environment. Specifically, the experimental condition operationalizes brain-based learning principles through the B.R.A.I.N.-B.A.S.E.D. framework (Hileman, 2006), which translates neuroscience-informed learning principles into learning design features. The experimental group engaged with a brain-based online learning design informed by the B.R.A.I.N.-B.A.S.E.D. framework, incorporating multimodal visualisation, structured repetition, active learning, emotional engagement, and interactive learning activities. Brain-based learning emphasizes alignment between learning strategies and cognitive processes such as attention, memory encoding, emotional engagement, and meaning-making (Caine & Caine, 1991; Jensen, 2005).

The B.R.A.I.N.-B.A.S.E.D. framework functions as a design schema that guides the development of online learning materials. It incorporates the following key principles as posited by Hileman (2006):

B (Brain's time clock): Learning is influenced by the brain's natural attentional rhythms, which fluctuate over short cycles. Learning activities are therefore designed to vary in format and intensity, avoiding prolonged passive exposure and maintaining learner engagement through periodic shifts in activity. This supports sustained attention and facilitates higher-order cognitive functioning during the learning process.

R (Repetition): Learning is reinforced through repeated exposure to content across multiple formats. Presenting information through videos, diagrams, summaries, and iterative review activities reinforces neural connections and supports long-term retention. Spaced repetition and varied practice further enhance memory consolidation.

A (Active learning): Learners must actively manipulate content through discussion, problem-solving, and reflective tasks. This participatory approach shifts the learner from a passive observer to an active processor. This deeper level of mental involvement strengthens memory pathways, increases self-confidence, and ensures the knowledge is better retained for practical application.

I (Images): Visual representations play a critical role in learning, as the brain processes visual information more efficiently than textual input. The integration of images, diagrams, animations, and video demonstrations supports comprehension, directs attention, and facilitates the encoding of complex information.

N (Novelty): Novel and unexpected elements stimulate the brain's reward system, which naturally heightens attention. Learning design incorporates variation, surprise, and creative presentation to sustain interest and enhance engagement.

B (Be color): The strategic application of colour enhances attention, comprehension, and memory by strengthening visual associations and guiding focus.

A (Automatic learning): Learning is influenced not only by conscious processing but also by non-conscious and affective factors. Learning environments are designed to create positive, engaging experiences that support implicit learning processes.

S (Social brain): Learning is inherently social. Opportunities for interaction, collaboration, and discussion are incorporated to enhance understanding, engagement, and retention.

E (Elicit emotions): Emotional engagement plays a critical role in attention and memory. Instructional strategies such as storytelling and scenario-based learning are used to evoke meaningful emotional

responses that strengthen learning.

D (Develop thinking skills): Higher-order thinking is promoted through problem-solving, decision-making, and real-world application tasks, enabling learners to transfer knowledge beyond the learning environment.

Together, the B.R.A.I.N.-B.A.S.E.D. framework provides a comprehensive guide for designing online learning environments that align with how learners process, retain, and apply information. In the context of basketball learning, these principles are operationalized through features such as multi-angle video demonstrations, slow-motion replay, annotated movement breakdowns, interactive discussions, and scenario-based tactical analysis, which collectively support both technical skill acquisition and decision-making processes.

In contrast, the control group experienced a conventional online learning design characterized primarily by content delivery through standard videos and textual materials with limited interaction and cognitive support. This contrast enables the study to isolate the effects of brain-based design principles design on learning processes. Specifically, the framework proposes that brain-based online design enhances cognitive processing, perceptual-motor integration, and learning motivation. This study then investigated the effects of these mediating processes on basketball technical skills, physical fitness, and motivation. Table 1 summarizes how the B.R.A.I.N.-B.A.S.E.D. framework was operationalized within the online learning environment, linking design features to learning mechanisms and expected outcomes.

Table 1. Operationalization of the B.R.A.I.N.-B.A.S.E.D. Framework

Principle	Design Feature	Example from Online Environment	Learning Mechanism	Expected Outcome
B – Brain's time clock	Pre-class activation, segmented learning	Introductory videos and guiding questions before each basketball module; short, structured learning segments	Schema activation; sustained attention	Improved comprehension of techniques and readiness for practice
R – Repetition	Multi-format repetition; spaced review	Layup and shooting techniques presented via standard video, slow-motion replay, multi-angle views, and diagrams; revisited before/after practice	Strengthening neural connections; memory consolidation	Improved technical skill accuracy and retention
A – Active Learning	Interactive tasks; reflective engagement	Discussion forums analysing gameplay; tactical decision-making questions; reflection on personal performance	Deep cognitive processing; knowledge construction	Higher-order understanding; improved skill application

Principle	Design Feature	Example from Online Environment	Learning Mechanism	Expected Outcome
I – Images & Visual Processing	Multimodal visualisation	Multi-angle demonstrations; slow-motion breakdowns; annotated diagrams of movements and tactics	Dual-channel processing; perceptual clarity	Better understanding of movement execution and spatial awareness
N – Novelty & Engagement	Varied formats; scenario-based tasks	Real match footage analysis; unexpected gameplay scenarios; simulation-style activities	Attention stimulation; increased motivation	Sustained engagement and improved learning motivation
B – Be Color (Visual Emphasis)	Colour-coded visual cues	Highlighting key movement phases and tactical roles using contrasting colours in diagrams and videos	Attention guidance; enhanced encoding	Faster recognition of key concepts; improved recall
A – Automatic Learning	Repeated exposure; implicit patterning	Continuous exposure to structured video demonstrations and movement sequences across modules	Non-conscious learning; pattern recognition	Internalisation of motor skills and smoother execution
S – Social Brain	Collaborative interaction	Peer discussions on tactics; forum-based analysis of gameplay; shared responses to prompts	Social constructivism; shared cognition	Deeper understanding; increased engagement
E – Elicit Emotions	Emotional and contextual design	Storytelling using real match scenarios, relatable player examples, and engaging content presentation	Emotional arousal; enhanced memory encoding	Increased motivation and retention
D – Develop Thinking Skills	Problem-based and scenario tasks	Tactical problem-solving tasks; analysing game situations and proposing strategies	Critical thinking; transfer of learning	Improved decision-making and tactical awareness

Method

This study employed a quantitative, pretest–posttest controlled experimental design to investigate the effects of brain-based online learning design within a blended basketball learning environment. The design was structured

to isolate the effects of the online learning component while maintaining consistency across all other aspects of learning. Both the experimental and control groups received identical basketball content, learning objectives, and face-to-face instruction, with the only difference being the design of the online learning environment. The use of a pretest–posttest structure further allows for the assessment of both within-group improvements and between-group differences over time, enhancing the internal validity of the findings.

Participants

The participants consisted of 100 undergraduate male students enrolled in a basketball elective course at a higher education institution. All participants were second-year students with comparable educational backgrounds and limited prior experience in formal basketball training, ensuring a relatively homogeneous baseline in terms of skill level and familiarity with the subject matter. Participants were from two intact classes, which were subsequently randomly assigned to either the experimental group ($n = 50$) or the control group ($n = 50$). This cluster randomisation approach was adopted to minimize potential contamination between groups while preserving the natural instructional setting. Such an approach is commonly used in educational research where individual randomisation is not feasible due to logistical constraints.

Intervention

The intervention was conducted over 12 weeks within a single academic semester. The total instructional time amounted to 24 hours, comprising 8 hours of online learning and 16 hours of face-to-face instruction. Both groups followed the same curriculum, which included basketball technical skills, tactical understanding, and gameplay strategies.

The face-to-face component focused on practical skill development, including dribbling, shooting, layups, and tactical drills, as well as gameplay and instructor-led feedback. This component provided opportunities for physical practice, skill execution, and corrective guidance, which are essential for motor skill development in basketball. The key distinction between the two groups lay in the design of the online learning environment.

In the experimental group, the online component was designed using the B.R.A.I.N.-B.A.S.E.D. framework, which integrates principles from brain-based learning theory into instructional design. The online modules incorporated multimodal visualisation, including slow-motion and multi-angle video demonstrations, annotated movement breakdowns, and tactical diagrams. Active learning was promoted through interactive discussion forums, reflective tasks, and scenario-based activities requiring students to analyse gameplay and make decisions.

Repetition and reinforcement were embedded through repeated exposure to key techniques across different formats and time points, while emotional engagement and novelty were introduced through real-game scenarios, storytelling elements, and varied instructional approaches. Additionally, cognitive scaffolding was provided through structured sequencing of content and guided prompts, supporting learners in progressively building their understanding. These features were designed to enhance cognitive processing, perceptual-motor integration, and learning motivation within the basketball learning context.

In contrast, the control group received online instruction covering the same content but delivered through a conventional format. The online materials consisted primarily of standard instructional videos, textual explanations, and demonstration-based content presentation. The learning environment in this condition functioned largely as a content delivery platform, with limited opportunities for interaction, multimodal engagement, or structured cognitive support. This distinction enabled the study to isolate the effects of brain-based learning design on learning processes and outcomes.

Measures

The study assessed three categories of learning outcomes: basketball technical skills, physical fitness, and learning motivation. Basketball technical skills and physical fitness assessments were conducted at two key points: a baseline evaluation in week 1 and a post-intervention evaluation in week 12. Learning motivation was assessed in week 12 only.

Technical Skills Rubrics

Basketball technical skills were evaluated using structured performance assessments focusing on moving dribble layups and five-point shooting accuracy. These assessments were designed to capture both the effectiveness and quality of skill execution. Scoring rubrics were developed based on multiple consultations with eight subject-matter experts to ensure that evaluation criteria were appropriate, comprehensive, and aligned with instructional objectives. The total scores range from 0 to 100 points.

A pilot study was conducted to evaluate the reliability of the scoring rubrics prior to the main study. Fifteen second-year male students from the university, who were not participating in the main study, completed both the moving dribble layup and five-point shooting assessments. Two trained raters independently scored all performances. Inter-rater reliability, assessed using intraclass correlation coefficients (ICC), yielded values of 0.91 for the moving dribble layup and 0.89 for the five-point shooting, indicating excellent agreement (Koo & Li, 2016). The pilot results confirmed that the scoring rubrics could reliably measure students' technical performance.

Physical Fitness Assessment

Physical fitness was assessed using standardised measures consistent with established, national fitness testing standards for university students in the country. These included four standardised assessments: (a) 1000-meter run measuring cardiovascular endurance (30% weight); (b) pull-ups measuring upper-body strength (30% weight); (c) sit-and-reach measuring flexibility (20% weight); and (d) 50-meter sprint measuring speed and agility (20% weight).

The scoring criteria enable precise quantification of performance changes in each fitness domain, ensuring a robust analysis of the effect of the intervention on physical fitness outcomes. Each component of the fitness assessment contributes to the overall score based on its respective weight. These measures provided an objective evaluation

of participants' physical capabilities.

Learning Motivation Measurement

Learning motivation was measured using the Instructional Materials Motivation Survey (IMMS), which is based on Keller's ARCS model of motivation (Keller, 2010). The 36-item instrument assesses four dimensions: attention, relevance, confidence, and satisfaction. Participants responded to items using a 5-point Likert-type scale, allowing for quantitative analysis of motivational changes. Evaluation of the IMMS motivation questionnaire confirmed instrument reliability. Cronbach's α coefficient yielded 0.89, indicating excellent internal consistency reliability.

Results

Preliminary Analysis on Baseline Equivalence

Prior to the intervention, baseline equivalence between the two groups was established. Statistical analyses indicated no significant differences in demographic characteristics, basketball technical skills, or physical fitness measures. This ensured that any observed differences in post-intervention outcomes could be attributed more confidently to the instructional design rather than pre-existing group differences.

Demographic Characteristics

The sample comprised 100 male undergraduate students enrolled in a basketball elective course, with a mean age of 20.4 years, a mean height of 172.9 cm, a mean weight of 66.1 kg, and a mean BMI of 22.2. Participants had limited recreational basketball experience (mean = 1.7 years) and no professional training background (see Table 2). All were free from physical illnesses or injuries that could interfere with sports participation, and all maintained full attendance throughout the intervention. Independent-samples t-tests, as presented in Table 2, indicated no significant differences between the experimental and control groups on any demographic variable (all $p > 0.05$), thereby confirming baseline equivalence.

Table 2. Participants' Demographic Characteristics

Characteristic	Experimental Group (n=50)	Control Group (n=50)	Total (N=100)	t-value	p-value
Age (years)	20.3±0.8	20.5±0.7	20.4±0.8	-1.35	0.180
Height (cm)	172.6±5.4	173.1±6.2	172.9±5.8	-0.43	0.665
Weight (kg)	65.8±8.9	66.4±9.3	66.1±9.1	-0.33	0.742
BMI (kg/m ²)	22.1±2.6	22.2±2.4	22.2±2.5	-0.21	0.837
Recreational basketball experience (years)	1.8±1.2	1.6±1.1	1.7±1.2	0.89	0.375

Note: Data presented as M±SD. Independent samples t-tests showed no significant differences between groups (all $p > 0.05$), confirming baseline equivalence. BMI = Body Mass Index.

Basketball Technical Skills

Basketball technical skills baseline assessment revealed no significant differences in moving dribble layup (31.8 ± 4.2 vs 30.9 ± 4.0 , $p = 0.266$) and five-point one-handed shoulder shooting performance (35.7 ± 4.6 vs 34.3 ± 4.3 , $p = 0.120$), with small effect sizes indicating minimal practical differences (see Table 3). Although the total technical score approached marginal significance (67.5 ± 6.8 vs 65.2 ± 6.5 , $p = 0.081$, $d = 0.35$), this difference remained within acceptable limits for experimental validity, ensuring that post-intervention skill improvements could be attributed to the intervention rather than pre-existing group disparities.

Table 3. Basketball Technical Skills Baseline Equivalence Testing

Basketball Technical Skills	Experimental Group (n=50)	Control Group (n=50)	t-value	p-value	Cohen's d
Moving dribble low-hand layup	31.8±4.2	30.9±4.0	1.12	0.266	0.22
Five-point one-handed shoulder shot	35.7±4.6	34.3±4.3	1.57	0.120	0.31
Total technical score (points)	67.5±6.8	65.2±6.5	1.76	0.081	0.35

Physical Fitness

Physical fitness baseline assessment similarly confirmed no significant differences across all fitness components (see Table 4). Independent samples t-tests revealed no significant differences in cardiovascular endurance (1000m run), muscular strength (pull-ups), flexibility (sit-and-reach), or speed (50m sprint), with all $p > 0.05$ and negligible effect sizes (all $d < 0.15$). The composite fitness scores of 61.2 ± 5.8 and 60.7 ± 6.1 for the experimental and control groups, respectively ($p = 0.669$), established adequate baseline equivalence.

Table 4. Physical Fitness Baseline Equivalence Testing

Physical Fitness Components	Experimental Group (n=50)	Control Group (n=50)	t-value	p-value	Cohen's d
1000m run (min:sec)	4:18±0:24	4:21±0:26	-0.61	0.543	0.12
Pull-ups (reps)	8.3±2.1	8.1±2.3	0.45	0.653	0.09
Sit-and-reach (cm)	9.8±4.2	10.2±4.5	-0.47	0.642	0.09
50m sprint (seconds)	7.85±0.42	7.89±0.38	-0.51	0.613	0.10
Total physical fitness score	61.2±5.8	60.7±6.1	0.43	0.669	0.08

Note: Data presented as $M \pm SD$. Independent samples t-tests revealed no significant baseline differences between groups (all $p > 0.05$). Physical fitness score calculated using a weighted formula: 1000m run (30%) + pull-ups (30%) + sit-and-reach (20%) + 50m sprint (20%).

No statistically significant differences were found between groups in terms of basketball technical skills or physical fitness, indicating that both groups were comparable prior to the intervention.

Normality Testing

Normality assessment through Shapiro-Wilk testing confirmed that all outcome variables met distributional assumptions for parametric analysis (see Table 5). All variables demonstrated non-significant Shapiro-Wilk statistics ($p > 0.05$), with skewness values ranging from -0.31 to 0.22 and kurtosis values ranging from -0.41 to -0.19 , justifying the use of independent samples t-tests for hypothesis testing.

Table 5. Normality Testing and Descriptive Statistics for Key Variables

Variable	Group	M±SD	Min-Max	Skewness	Kurtosis	Shapiro-Wilk	p-value
Basketball Technical Skills							
Total technical score	Experimental	76.8±8.2	62-93	-0.18	-0.41	0.978	0.421
	Control	68.5±7.6	54-84	0.12	-0.35	0.982	0.634
Physical Fitness							
Total fitness score	Experimental	65.7±6.3	52-78	-0.08	-0.28	0.986	0.745
	Control	64.9±5.9	51-76	0.15	-0.22	0.979	0.458
Learning Motivation							
IMMS total score	Experimental	4.21±0.45	3.28-4.94	-0.31	-0.19	0.974	0.328
	Control	3.58±0.52	2.67-4.72	0.22	-0.33	0.981	0.589

Effects on Basketball Technical Skills

The statistical analysis revealed significant differences between groups across all basketball technical skill measures following the intervention (see Table 6). The experimental group demonstrated superior overall performance with a mean score of 76.8 ± 8.2 points compared to the control group's 68.5 ± 7.6 points, yielding a substantial between-group difference ($t=5.72$, $p<0.001$). This 8.3-point advantage represents a meaningful improvement in comprehensive basketball proficiency, supported by a large effect size (Cohen's $d=0.92$) that indicates substantial practical significance. The highly significant p-values across all measures confirm that the observed differences exceed statistical chance, providing strong evidence for the effectiveness of the brain-based online learning intervention in enhancing technical skill acquisition.

The component-level analysis revealed consistent patterns of superiority favoring the experimental condition. The moving dribble low-hand layup assessment showed the experimental group achieving 35.6 ± 4.2 points versus the control group's 32.1 ± 3.9 points ($d=0.91$), while the five-point one-handed shoulder shot demonstrated an even larger disparity with scores of 41.2 ± 5.1 and 36.4 ± 4.8 , respectively ($d=0.98$). The exceptionally large effect sizes across both fundamental skills indicate that the intervention produced practically meaningful improvements in discrete technical competencies. These findings suggest that brain-based instructional strategies enhanced both dynamic movement coordination and static shooting precision, demonstrating the comprehensive effect of the intervention on diverse basketball skill domains rather than selective improvement in isolated techniques.

Table 6. Comparison of Basketball Technical Skills Between Groups

Assessment items	Experimental	Control	t value	p value	Cohen's d
Overall skill score	76.8±8.2	68.5±7.6	5.72	<0.001***	0.92
Moving dribble low-hand layup	35.6±4.2	32.1±3.9	4.38	<0.001***	0.91
Five-point one-handed shoulder shot	41.2±5.1	36.4±4.8	4.75	<0.001***	0.98

Note: The total score of skills is 100 points. The technical evaluation of the moving dribble layup and five-point one-handed shoulder shot is 50 points, respectively. *** indicates that $p < 0.001$.

Figure 2 illustrates the differential effect of brain-based online learning on basketball technical skills development over the intervention period. The visualization reveals that both groups demonstrated measurable improvement from baseline to post-intervention, yet the magnitude of enhancement varied considerably between conditions. The experimental group exhibited substantial skill advancement, progressing from an initial mean score of 67.5 points to 76.8 points, representing a 9.3-point improvement that corresponds to a 14% increase in technical proficiency. In contrast, the control group showed more modest gains, advancing from 65.2 points to 68.5 points, yielding a 3.3-point improvement equivalent to a 5% enhancement. The statistical analysis confirmed the significance of between-group differences in improvement trajectories ($p < 0.001$), indicating that the brain-based online learning intervention produced substantially greater skill development compared to the conventional online learning method.

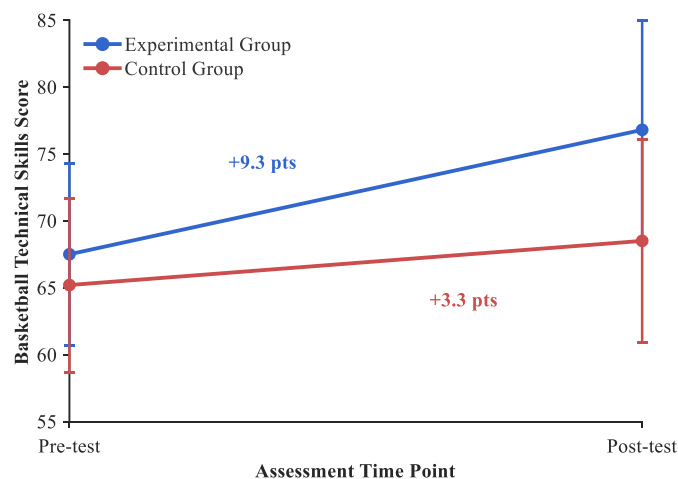


Figure 2. Technical Skills Improvement

Figure 3 demonstrates a moderate positive correlation between moving dribble layup and one-handed shooting performance across both experimental ($r = 0.446$) and control groups ($r = 0.411$), with an overall correlation of $r = 0.555$. The moderate correlation coefficients indicate that while these basketball skills share some underlying motor coordination components, they maintain distinct technical requirements and can develop somewhat independently. The scatter plot reveals clear distributional separation between groups, with experimental participants predominantly positioned in the upper-right region representing superior performance in both skill domains, while control group students were more dispersed across lower performance ranges.

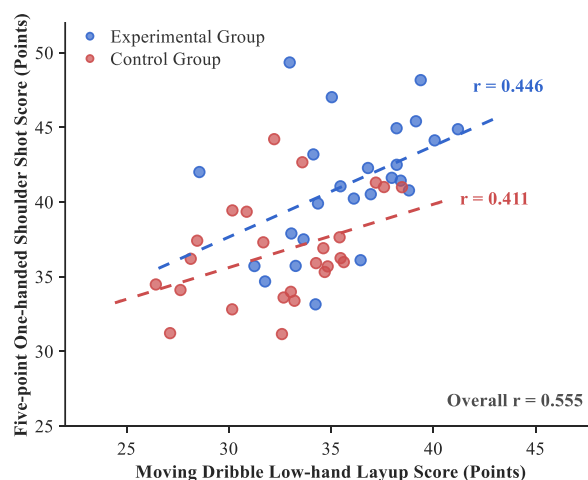


Figure 3. Individual Technical Skills Correlation

The similar correlation magnitudes between groups suggest that the fundamental relationship between dribbling and shooting abilities remained consistent regardless of instructional approach. However, the spatial elevation of the experimental group distribution demonstrates that brain-based online learning enhanced overall skill performance without artificially inflating the interdependence between these technical competencies. This pattern indicates that the intervention effectively improved both skills while preserving their natural relationship structure, suggesting that enhanced motor learning facilitated concurrent but appropriately independent development of distinct basketball abilities.

Effects on Physical Fitness

The physical fitness analysis revealed significant within-group improvements for both experimental and control groups ($p < 0.001$), with moderate to large effect sizes ($d = 0.72$ and $d = 0.68$, respectively). The experimental group improved from 61.2 ± 5.8 to 65.7 ± 6.3 points, while the control group progressed from 60.7 ± 6.1 to 64.9 ± 5.9 points. However, between-group comparison showed no significant differences in post-intervention fitness scores ($t = 0.87$, $p = 0.385$, $d = 0.14$). Both groups demonstrated equivalent fitness enhancement, suggesting that the offline training components, which remained consistent across conditions, were the primary determinant of physical fitness improvements regardless of the online learning approach employed (see Table 7).

Table 7. Comparison of Physical Fitness Scores Between Groups

Metric	Group	Mean before test $\pm$ standard deviation	Mean post-test $\pm$ standard deviation	t-value	p-value	Cohen's d
Overall fitness score	Experimental group	61.2 $\pm$ 5.8	65.7 $\pm$ 6.3	6.89***	<0.001	0.72
	Control group	60.7 $\pm$ 6.1	64.9 $\pm$ 5.9	5.92***	<0.001	0.68
Intergroup differences	-	-	t=0.87	p=0.385	-	0.14

Note: The total physical fitness score was calculated by weighted calculation of 1000-meter run (30%), pull-up (30%), sit-and-reach (20%) and 50-meter run (20%); *** indicates that $p < 0.001$.

Figure 4 demonstrates consistent patterns across individual physical fitness components, with no significant differences observed between experimental and control groups in any of the four assessed domains (all $p > 0.05$). The component-level analysis confirms that the non-significant overall fitness findings reflected uniform performance across cardiovascular endurance, muscular strength, flexibility, and speed measures rather than selective improvements in specific fitness dimensions. While both groups demonstrated measurable gains from baseline levels, the magnitude of improvement remained comparable across all physical fitness components, suggesting that the offline training regimen served as the primary determinant of fitness enhancement regardless of the online learning approach. This uniform distribution of non-significant differences across diverse fitness domains reinforces the conclusion that brain-based online learning interventions may be more effective for cognitive and skill-based outcomes than for physiological adaptations that depend primarily on physical training volume and intensity.

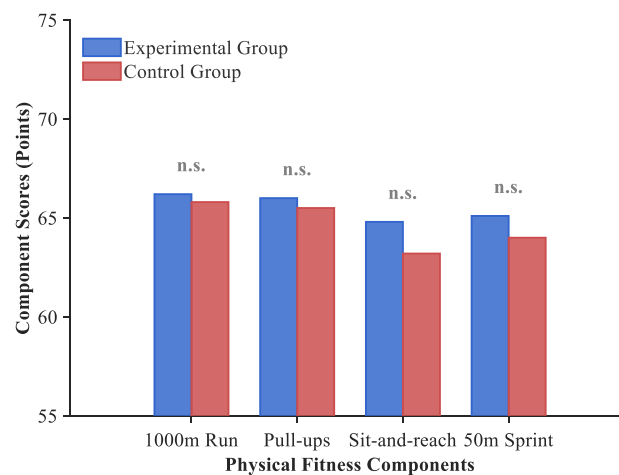


Figure 4. Physical Fitness Components Comparison

Figure 5 provides visual confirmation of the non-significant between-group differences in physical fitness through individual score distributions.

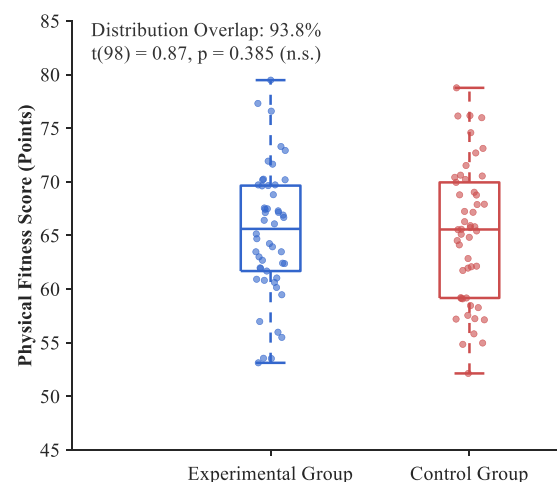


Figure 5. Individual Fitness Improvement Distribution

The extensive overlap of 93.8% between experimental and control group distributions corroborates the statistical finding of no significant difference ($t=0.87$, $p=0.385$), demonstrating that the majority of participants from both groups achieved comparable fitness levels regardless of instructional approach. The similar distribution patterns, central tendencies, and variability ranges observed across treatment conditions reinforce the conclusion that physical fitness improvements were primarily driven by the consistent offline training regimen rather than the differentiated online learning components. This individual-level analysis validates the group-level statistical findings and supports the interpretation that brain-based online learning interventions may have a limited impact on physiological outcomes that depend fundamentally on physical exercise intensity and volume.

Effects on Learning Motivation

Learning motivation assessment revealed significant between-group differences across all four IMMS dimensions, with the experimental group demonstrating substantially higher motivation levels than the control group (Table 8). All motivational components—confidence, attention, satisfaction, and relevance—achieved statistical significance at the $p<0.001$ level with large effect sizes (Cohen's $d > 1.0$), indicating that brain-based online learning interventions produced practically meaningful enhancements in student motivation. The most pronounced improvements occurred in satisfaction ($d=1.23$) and confidence ($d=1.18$) dimensions, suggesting that the interactive and scaffolded nature of brain-compatible online learning design particularly enhanced students' perceived competence and learning enjoyment. These comprehensive motivational gains across all measured dimensions provide compelling evidence that brain-based online learning approaches not only improve skill acquisition but also foster positive affective outcomes essential for sustained engagement in physical education contexts.

Table 8. Comparison of Learning Motivation Dimensions Between Groups

Motivational dimension	Experimental group (M±SD)	Control group (M±SD)	t value	p value	Cohen's d
Confidence	4.32±0.38	3.71±0.42	7.36	<0.001***	1.18
Attention	4.15±0.41	3.49±0.45	6.89	<0.001***	1.12
Satisfaction	4.28±0.35	3.62±0.39	7.91	<0.001***	1.23
Relevance	4.05±0.37	3.53±0.41	6.22	<0.001***	1.05

Note: The IMMS questionnaire used a 5-point Likert scale (1 = incorrect, 5 = very correct); *** indicates that $p < 0.001$.

Statistical Results and Theoretical Verification

The comprehensive statistical analyses conducted across multiple outcome domains provide robust evidence for the differential effects of brain-based online learning interventions in physical education contexts. The results demonstrate a clear pattern of domain-specific effectiveness that aligns with theoretical predictions regarding the mechanisms of brain-compatible learning design.

Physical fitness outcomes revealed no significant between-group differences ($t=0.87$, $p=0.385$), with both experimental and control groups achieving comparable improvements from baseline levels. The high distribution overlap (93.8%) and small effect size (Cohen's $d=0.14$) confirm that physiological adaptations were primarily driven by the standardized offline training regimen rather than the differentiated online learning approaches. This finding supports the hypothesis that brain-based strategies have a limited effect on outcomes that depend fundamentally on physical exercise volume and intensity.

In contrast, basketball technical skills exhibited substantial between-group differences, with the experimental group demonstrating superior performance across all measured competencies. Large effect sizes for total technical skills ($d=1.21$), moving dribble layup ($d=0.94$), and five-point shooting ($d=1.02$) indicate practically meaningful improvements attributable to the brain-based online learning intervention. Sub-component analysis revealed that technical evaluation scores, representing movement standardization and form execution, showed the most pronounced improvements, suggesting that multi-sensory stimulation and cognitive processing optimization primarily enhanced motor learning consolidation.

Learning motivation assessment provided the most compelling evidence for intervention effectiveness, with all four IMMS dimensions achieving significance at the $p<0.001$ level and large effect sizes exceeding $d=1.0$. The comprehensive motivational enhancement across confidence, attention, satisfaction, and relevance dimensions validates the emphasis of the B.R.A.I.N. B.A.S.E.D. on emotional engagement and novelty-seeking as fundamental components of effective instruction. These findings collectively verify that brain-based online learning interventions are most effective for cognitive and affective outcomes requiring active mental processing, while maintaining limited influence on purely physiological adaptations.

Discussion

This discussion shows that the effects of the intervention were driven mainly by learning design rather than technology alone. Brain-based online learning improved basketball technical skills and learning motivation, but not physical fitness, suggesting that design features such as multimodal visualisation, repetition, and interactive engagement are more effective for cognitive, affective, and skill-based outcomes than for physiological adaptation.

Learning Design as the Key Determinant of Digital Learning Effectiveness

The findings reinforce a central argument in educational computing that learning outcomes are shaped more by learning design than by the technology itself (Clark, 1983; Kozma, 1994). Despite both groups receiving identical content and face-to-face instruction, the experimental group demonstrated superior outcomes, indicating that the observed effects can be attributed to the design of the online learning environment. This finding is consistent with contemporary research emphasizing that effective digital learning environments must be intentionally designed to support learning processes, rather than simply deliver content (Alamri et al., 2021; De Bruijn-Smolters & Prinsen, 2024). Similarly, research on blended learning highlights that alignment between online and offline components

is critical for achieving meaningful learning outcomes (Garrison & Kanuka, 2004; Hrastinski, 2019). The present study extends this line of work by demonstrating that brain-based design principles can provide a systematic approach to structuring such environments, particularly in embodied learning contexts.

Enhancement of Basketball Technical Skill Acquisition

The significant improvement in basketball technical skills observed in the experimental group can be explained through the interaction between learning design and perceptual-motor learning processes. The use of multimodal visualisation, including slow-motion replay, multi-angle demonstrations, and annotated movement breakdowns, supports learners in developing more precise internal representations of movement patterns. From a neuroscientific perspective, such multimodal input facilitates multisensory integration, where information processed across visual and motor systems is combined to enhance perceptual accuracy and learning efficiency (Shams & Seitz, 2008; Stein & Stanford, 2008). This integration supports the formation of coherent neural representations that underpin skilled performance. In motor learning contexts such as basketball, these representations are critical for coordinating perception, decision-making, and movement execution.

Moreover, the embedded structured repetition aligns with principles of deliberate practice (Ericsson, 2001). At the neural level, repeated and varied practice supports experience-dependent neuroplasticity, strengthening and reorganizing neural circuits involved in motor skill learning and motor control (Dayan & Cohen, 2011). The combination of repetition, variation, and feedback in the online environment facilitates both the consolidation and refinement of motor skills, enabling learners to transfer these skills to dynamic gameplay situations.

Moderate correlations between dribbling and shooting skills ($r = 0.446\text{--}0.555$) suggest shared underlying motor coordination, yet independent skill development. This pattern indicates that the intervention enhanced fundamental movement literacy while preserving the specificity of technical competencies. Overall, these findings extend prior research demonstrating that brain-based pedagogical principles can enhance educational outcomes (Akyürek & Afacan, 2013b; Lagoudakis et al., 2022; Terblanche et al., 2026), and provide new evidence that such principles translate effectively from cognitive classroom contexts to motor skill domains in physical education.

Motivation as a Central Mechanism

The comprehensive enhancement of learning motivation across all IMMS dimensions represents one of the most significant findings of this study, highlighting how brain-based online learning transforms students' affective engagement. All four dimensions—confidence ($d = 1.18$), attention ($d = 1.12$), satisfaction ($d = 1.23$), and relevance ($d = 1.05$)—achieved statistical significance ($p < 0.001$), with large effect sizes exceeding $d = 1.0$. These results align with Keller's (2010) ARCS model, which posits that effective instruction must address attention, relevance, confidence, and satisfaction to optimise learner motivation. The findings also support Jensen's (2005) framework, which emphasises emotional engagement and novelty as drivers of neural activation and learning consolidation.

The pronounced improvements in satisfaction and confidence suggest that the B.R.A.I.N. B.A.S.E.D. framework, through features like inspirational narratives, visual imagery, and incremental skill building, effectively boosted perceived competence and learning enjoyment. Equally important are the gains in attention and relevance, which address persistent challenges in online education. Unlike traditional digital instruction that often lacks sustained engagement, the brain-based module's use of interactive elements, multi-angle demonstrations, and contextualised content appears to have enhanced meaning-making and attentional focus. The novelty elements, including basketball simulation games and innovative drill variations, likely sustained student interest throughout the intervention period. From a neuroscientific perspective, motivation and learning are closely linked through the brain's reward and attentional systems, which influence both engagement and memory formation (Hidi, 2016; Luria, 2021). Elements such as novelty, emotional engagement, and interactive tasks likely activated reward-related neural pathways, enhancing learners' attention and willingness to engage with the content. Research suggests that emotionally salient and rewarding experiences can facilitate dopaminergic modulation, which strengthens memory encoding and supports sustained engagement (Shohamy & Adcock, 2010). Taken together, the motivational gains likely served as mediating variables contributing to improved skill acquisition, as increased motivation typically leads to greater practice intensity, attentiveness, and persistence. These findings reinforce the value of brain-based pedagogical principles in addressing both cognitive and affective learning needs within technology-enhanced physical education contexts.

Limited Effects on Physical Fitness

In contrast to the significant effects observed for technical skills and motivation, the intervention did not produce a significant difference in physical fitness outcomes. The absence of significant between-group differences in physical fitness outcomes offers critical insights into the differential effects of brain-based online learning across educational domains. Both experimental and control groups showed comparable improvements in cardiovascular endurance, muscular strength, flexibility, and speed ($t = 0.87$, $p = 0.385$, Cohen's $d = 0.14$), with a high distribution overlap (93.8%), indicating that physiological adaptations were primarily driven by the standardized offline training regimen rather than the differentiated online learning strategies.

This finding aligns with established exercise physiology principles, which posit that improvements in physical fitness depend primarily on training volume, intensity, and progressive overload (Kumar & Vinayakan, 2024; Palma-Muñoz et al., 2021), rather than the instructional approach used. It also supports the view that brain-compatible strategies are most effective for outcomes involving active cognitive processing, memory consolidation, and neural engagement (Boles, 2025; Jensen, 2005), rather than for direct physiological conditioning. Although learning design can influence cognitive and affective processes, adaptations in endurance, strength, and speed are largely driven by the biomechanical, cardiovascular, and metabolic demands of physical activity. As both groups completed the same amount of face-to-face physical training (16 hours), similar fitness outcomes would be expected despite differences in online learning design. Neural adaptations may enhance motor coordination and movement efficiency; however, as noted by Spiering et al. (2021), measurable improvements in physical fitness require sustained physical exertion performed at sufficient intensity and duration.

Conclusion

The findings of this study contribute to educational computing research by demonstrating how theory-driven learning design can be grounded in both learning sciences and neuroscience perspectives. Specifically, the B.R.A.I.N.-B.A.S.E.D. framework provides a structured approach for designing digital learning environments that align with how the brain processes, integrates, and retains information. By transforming the online component from a passive content delivery platform into an active, cognitively and affectively engaging learning environment, the brain-based design facilitated deeper processing, improved perceptual-motor integration, and strengthened learner motivation. By linking design features to underlying neural mechanisms related to attention regulation, multisensory processing, reward and emotion, social cognition, memory consolidation, and experience-dependent neuroplasticity, the study extends existing work in educational computing beyond behavioural outcomes to include process-level explanations of learning. This aligns with emerging calls for more integrative approaches that connect learning design with cognitive and neural processes.

Importantly, the study demonstrates that online learning design can effectively support learning in embodied domains such as basketball, where performance depends on the integration of cognitive, affective, and motor processes. This finding extends the scope of educational computing research beyond traditional cognitive domains and provides evidence that theory-driven digital environments can enhance both understanding and performance in skill-based learning contexts. Overall, the study contributes to the field by offering a design-oriented, empirically validated framework for integrating brain-based learning principles into online environments within blended learning. The findings provide practical and theoretical insights for educators seeking to design more effective and engaging digital learning experiences in physical education and beyond.

Limitations and Future Research

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the study was conducted within a single institutional context with a relatively homogeneous sample of undergraduate male students. While this supports internal validity, it may limit the generalizability of the findings to other populations, such as different genders, age groups, educational levels, or cultural contexts. Future research should replicate the study across diverse settings to enhance external validity. Second, while the study provides evidence of the effectiveness of brain-based learning design, it does not directly measure the underlying cognitive and neural processes proposed in the conceptual framework. The interpretation of mechanisms such as cognitive processing and perceptual-motor integration is therefore inferred rather than empirically tested. Future research could incorporate process-oriented measures, such as cognitive load assessments, eye-tracking, or neurophysiological methods, to provide more direct evidence of these mechanisms. Third, the study focused on a specific sport, basketball, which involves particular types of motor and cognitive demands. While the findings are promising, further research is needed to determine whether the observed effects generalize to other sports or embodied learning domains with different skill requirements. Finally, the study examined the overall impact of the B.R.A.I.N.-B.A.S.E.D. framework as a whole. Future research could adopt a more granular approach by isolating and testing the effects of individual design components, such as multimodal visualisation, repetition, or

social interaction, to better understand their relative contributions to learning outcomes. Building on these limitations, future research should continue to explore how theory-driven learning design can be integrated with emerging technologies, such as artificial intelligence and adaptive learning systems, to further personalise and optimise learning experiences. In particular, investigating how digital systems can dynamically adjust learning design based on learners' cognitive and affective states represents a promising direction for advancing educational computing research.

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