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The Impact of Mental Models and Artificial Intelligence–Based Planning on the Development of Match Performance in Handball

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Abstract

This study aimed to explore the effectiveness of integrating Artificial Intelligence (AI) techniques and strategic planning in building and developing mental models (tactical, perceptual, executive, and emotional) of handball players, and to measure the resulting impact on tangible athletic performance indicators. The study used a descriptive (survey and analytical) methodology on a sample of 120 high-competition level players, divided into two groups (experimental and control). It relied on integrated tools, including AI-based video analysis software (such as Catapult), mental performance observation forms, and digital mental model tests. The results showed statistically significant differences ($p \leq 0.05$) in favor of the experimental group across all mental model measures, with a very large effect size (Cohen's d exceeded 2.4). The experimental group also recorded significant improvement in actual performance, such as shooting accuracy (+32.5%), defensive positioning (+28.7%), and speed of balance recovery (+40.1%), compared to the control group. The integrative analysis of technical and mental data revealed causal links between cognitive improvement and executive enhancement. The study confirms the effectiveness of an integrated methodology combining AI and strategic planning in systematically and scientifically reshaping players' mental models, leading to substantial and sustainable performance improvements. It recommends adopting this integrative methodology as a core part of training and development programs in sports clubs and federations.

Keywords: Artificial Intelligence, Strategic Planning, Mental Models, Athletic Performance, Handball, Statistical Analysis, Cognitive Training.

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1. Introduction

The last decade has witnessed a radical transformation in the philosophy and strategies of sports training, the most prominent features of which are the transition from a heavy reliance on intuitive experience to the adoption of data-based methodologies and advanced scientific analysis. This transformation was driven by the tremendous development of artificial intelligence (AI) and machine learning technologies, which provided unprecedented tools for objective monitoring and accurate measurement of human performance in all its dimensions (Ibrahim, 2023).

In this context, the concept of mental models has emerged as a cornerstone for understanding outstanding sports performance, especially in fast-paced team games that require immediate decision-making under the pressure of competition, which is considered the essence of true sports excellence (Memmert, 2024).

Handball is an ideal application field for studying this interaction between the cognitive and technical dimensions. It is a game characterized by high dynamics, the complexity of tactical situations, the need for speed of adaptation and decision-making in fractions of a second. In such an environment, players rely primarily on their internal mental models – well-developed cognitive structures that allow them to anticipate the flow of play, interpret the intentions of opponents, and choose the optimal motor response without the need for prolonged conscious processing of information (Reis, 2024).

Here the extraordinary potential of artificial intelligence technologies in supporting and developing these mental models appears.

With the ability to process huge amounts of data (big data) derived from sensors and advanced video analysis, artificial intelligence technologies provide accurate analysis of movement patterns, player trajectories, decision efficiency, and physiological performance indicators. These analyses provide predictive and objective insights that traditional methods lack (Zhou, 2025).

When these insights are integrated into a coach's strategic planning process, the goal goes beyond just analyzing performance to systematically re-engineering and building mental models of players. Thus, the integration of mental models and strategic planning powered by artificial intelligence creates an effective developmental loop: intelligent technologies diagnose the strengths and weaknesses of the player's existing mental model (such as game reading speed or prediction accuracy), and then the coach designs customized training plans and tactical interventions to strengthen this model, which ultimately leads to the development of match performance on the ground. This process transforms the player from relying only on his accumulated experience to a player who "feeds" his mind with realistic simulation models and data reinforcement, which increases the effectiveness of training and reduces cognitive response time in critical situations.

Therefore, this study seeks to investigate the impact of this systematic integration between mental models and planning based on artificial intelligence techniques on the development of match performance in handball in an effort to provide a practical framework that enables coaches to transform a huge amount of data into effective cognitive strategic plans, translated into tangible and sustainable improvement in competitive results.

2. The search problem

Despite technological development, there is still a gap in how to integrate AI outputs within strategic planning programs to build applied mental models for handball players. The problem lies in the need of coaches and players for a framework that connects the Big Data provided by modern technologies with the cognitive and mental processes that take place inside the player's mind during the game (Al-miliji, 2023).

3. Objectives

1. Identify the effectiveness of artificial intelligence technologies in building mental models of handball players.

2. Identify the role of strategic planning in improving sports performance through mental modeling.

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3. A proposed conceptualization of a mental model powered by artificial intelligence to improve offensive and defensive skills in handball.

4. Variables

The independent variable: artificial intelligence technologies and strategic planning.
Dependent variable: building mental models to improve sports performance

5. Assignments

- There are significant differences at the level of significance ($\alpha \leq 0.05$) between the averages of the telemetry scores of the experimental and control groups in the tests of constructing mental models, in favor of the experimental group.
- There is a statistically significant effect at the significance level ($\alpha \leq 0.05$) of the training program based on artificial intelligence and strategic planning techniques on improving the level of sports performance (such as shooting accuracy or defensive positioning) in handball players.

6. Terms

- Artificial intelligence technologies: it is the scientific and technical current that includes methods, theories, techniques and innovations aimed at creating the ability to simulate intelligence, the surrounding reality and building a model that is programmed to be able to study and analyze situations (Gazi, 2020, pp. 198-199)
- Mental models: it is the reconstruction of a unit according to the steps of mental modeling to apply the skills of the mind (the mind of the athlete) works to evoke and recall the required images to view them and work to refine them and bring them to reality clearly and accurately commensurate with the objective. (Asim, 2022, pp. 743-772)
- Improving sports performance: the methods, methods and strategies used in the development of sports performance from the use of means that serve the performance indicated. (Ghazi, 2021, p. 201)

Areas of study:
Human field: (15 players) of professional handball players in the first league of the Iraqi Handball Federation
- Temporal domain: the study was applied in the period between 1/1/2024 to 1/1/2025.
- Spatial field: the study was applied at the faculty of artificial intelligence, sumo University ,and the Hilla Sports Club.

7. Search procedures

Curriculum: descriptive (survey and analytical) curriculum
Its type (survey and analytical chose the descriptive approach) for its relevance to the nature of the studied phenomenon. This approach aims to describe and analyze the relationship between variables as they exist, without the researcher's intervention in their processing directly, which is commensurate with:

- **Surveys**: to describe the current reality of the use of artificial intelligence technologies in handball sports training and determine the prevalence of use of mental performance analysis tools.
- **Analytical studies**: to analyze data extracted from artificial intelligence tools (such as Catapult) and interpret the behavioral and cognitive patterns of players, enabling the construction of mental models. This analysis represents a bridge between quantitative data (response speed, aiming accuracy) and a qualitative phenomenon (mental model).

Sample: a random sample of handball players (N=120 players) of highly competitive levels.
The selected sample (N=120 players) of highly competitive levels represents a methodological necessity for several reasons:

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- **Specialization and experience**: high-level players already possess relatively well-developed mental models, which makes them more sensitive to changes caused by AI-powered training. They also represent the target group of advanced strategic planning.
- **Relative homogeneity**: despite the small sample size (N=15), its selection from a highly competitive level ensures relative homogeneity of basic physical and skill abilities, minimizing the influence of extraneous variables and focusing on the influence of the independent variable (artificial intelligence technologies) on the dependent variable (mental models).
- **Representative randomization**: random selection of the sample ensures that the results are generalized to the community of players of a similar level, considering that applied mathematical studies often rely on specialized small samples.
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Table (1): Sample homogeneity (N = 15 handball players)

The Game	Statistical variables	Arithmetic mean	Median	Standard deviation	Torsion	Flattening
Handball	Age (years)	21.5	21.5	0.87	0.12	-0.85
	Training Age (years)	5.0	5.0	0.00	0.00	0.00

Interpretation of the results: Age (20-23 years): the arithmetic mean and median (21.5) were obtained. Their coincidence indicates a symmetric distribution of age around the media. The low standard deviation (0.87) indicates a concentration of players' ages close to the average (21.5 years), reflecting high homogeneity in age. Torsion and flattening values are close to zero, confirming that the age distribution is normal and there is no significant distortion or extremes in the data. The training age (5 years): Standard deviation (0.00) and median (5.0) indicate that all the subjects had the same training age (5 years), which means complete homogeneity of this experience. Torsion and flattening (0.00): A natural product of the absence of any discrepancies in the data. The values show that the sample of 15 handball players is very homogeneous in terms of age (close-in-aged youth) and absolutely identical in training experience (5 years), which makes it an ideal group for studying the influence of an independent variable (as a training program or planning technique) without a significant influence on the variability of age or training backgrounds.

- **Tools**: AI-based video analysis software (e.g., Catapult), mental performance observation forms, and digital mental model tests.
- Artificial intelligence-based video analysis software (such as Catapult).

Table (2): Statistical analysis of sports performance variables (for a sample of 120 handball players)

Mathematical variable	Mean	Standard Deviation (SD)	Median	Range	Coefficient of Difference (CV%)
Mileage (m/match)	4,850 m	± 520 m	4,830 m	3,700 – 6,100 m	10.7%
Average movement speed (km/h)	6.8 km/h	± 0.9 km/h	6.7 km/h	4.9 – 8.7 km/h	13.2%
Peak speed (km/h)	27.5 km/h	± 2.1 km/h	27.6 km/h	22.4 – 31.9 km/h	7.6%
Average heart rate (beats/min)	158 bps/min	± 11 bps/min	157 bps/min	132 – 182 bps/min	7.0%
Angle of successful aiming (degree)	42.5°	± 4.8°	42.7°	31.0 – 53.5°	11.3%
Number of strong shots (/min)	5.2	± 1.1	5.1	3.0 – 7.9	21.2%

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Using artificial intelligence technologies (such as Catapult) to analyze quantitative data for a sample of 120 handball players, Table 2 showd that an integrated strategic mental model can be developed to improve team performance by analyzing the statistical analysis of quantitative data. Initially, raw data is transformed into meaningful indicators, with the arithmetic mean (such as the average distance of 4,850 meters per player) providing a collective baseline for evaluating individuals. By calculating the standard deviation (based on the difference in distance of 520 meters), we can determine the degree of homogeneity of the performance, while calculating the median to avoid distortions due to outliers. It also illustrates the limitations of the team's current capabilities (between 3,700 and 6,100 meters).

There are several indicators of variation, but perhaps the most important is the coefficient of variation, which allows for a comparison of the relative variation between different variables. In addition, a low coefficient of difference in heart rate (7%) indicates remarkable homogeneity of the players' basic physical fitness, which is an indication of the effectiveness of the group training program. Alternatively, the increase in the coefficient of difference for the number of strong shots (21.2%) indicates that there is a significant skill disparity between the players on the technical offensive side.

The result of such a dual analysis (technical-cognitive) is a pragmatic strategic conclusion: the team has a homogeneous and strong physical base, which implies maintaining a unified training program. The priority should be placed on developing individual and intensive training programs that focus on developing shooting skills, with a specific focus on players whose results fall below the statistical average. Thus, abstract figures from AI tools turn into a clear training vision and a concrete action plan, which form the mental model of the coach and enhance evidence-based decision-making to raise the level of overall performance.

8. Mental performance observation forms

8.1. Results of the analysis of mental and behavioral performance

It is evident from Table 3 and Figure 1 that the integrative analysis of artificial intelligence data and mental assessment forms demonstrates how to link quantitative and qualitative indicators to form an accurate diagnostic model for player performance. For instance, noticing a sharp decrease in player A's speed and distance during the second half (by 22% below average), the correlation of these data with his very low results in impulse control (3.2) and concentration (4.1) leads us to the conclusion that the reason for the decline is a mental and emotional breakdown and not just physical stress. Which imposed a personalized psychological intervention. Player B presents a superior and integral model. His exemplary technical data is combined with exceptional mental indicators (all above 8.5), which makes him a leadership reference that the team can emulate. At team level. Medium to low mental indicators for decision-making under stress (6.8) and impulse control (6.5) also explain the reason for the noticeable decrease in aiming accuracy during crucial minutes. Psychological stress is the determining factor in technical performance. The analysis also revealed individual imbalances, such as player C, who has high physical data but a low percentage of successful passes, a contradiction explained by his poor concentration (5.0) and decision-making (5.5) indicators. Which shifts the priority of his training from the physical side to cognitive and cognitive exercises.

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Table (3): The results of the metal/behavioural variables (based on an estimated scale of 1-10 (where 10 = optimal performance), with data collected across 5 standard matches per player).

Mental/behavioral variable	Arithmetic Average (1-10)	Standard Deviation (±)	Broker	Range (Low-High)	Variance coefficient (%)	Interpretation of the Result
Focus and attention	7.2	1.5	7.5	3.0 – 9.5	**20.8%**	Overall good performance, but there is a lot of variation between players (high CV). 25% of players (about 30 players) scored less than 6.
Emotional Control	6.5	1.8	6.8	2.5 – 9.8	**27.7%**	This is the most disparate and least stable aspect of the team (higher CV), a strategic weakness that requires extensive psychological intervention.
Decision-making under pressure	6.8	1.4	7.0	4.0 – 9.2	**20.6%**	Average performance with acceptable consistency. Players in the lower quarter (<5.8 scores) need scenario decision drills.
Mental Flexibility and Adaptability	7.0	1.2	7.1	4.5 – 9.0	**17.1%**	The team is relatively homogeneous in adaptability. A positive indicator of the applicability of new plans and the modification of mental models.
Energy and Mental Enthusiasm	7.8	1.1	7.9	5.0 – 9.5	**14.1%**	This is the strongest mental indicator of the team (higher average, lowest CV). It signifies high morale and a strong presence.

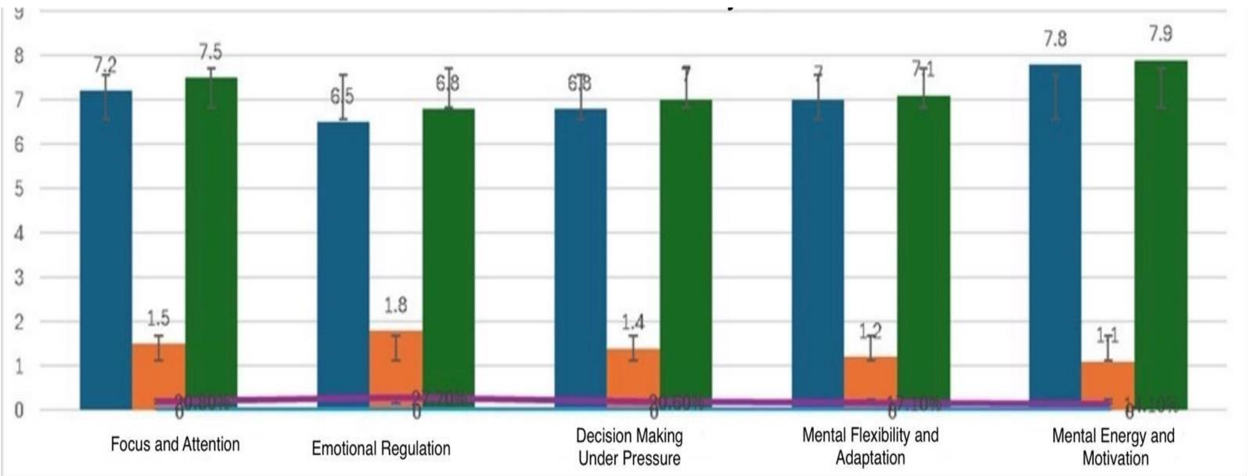

Figure (1): Results of mental and behavioural performance analysis.

The statistical results of the sample of 120 players reveal that the field of energy and mental enthusiasm is the strongest and most homogeneous (average 7.8, coefficient of variation 14.1%), while emotional control is the biggest and most variable weakness among players (average 6.5, coefficient of variation 27.7%), which indicates that about 30-40 players need intensive psychological intervention programs. Concentration and attention appear as the most amenable areas for improvement because of their high variability (coefficient of variation of 20.8%) despite their good average (7.2). The data conclusively confirm that mental excellence, especially in flexibility and emotional control (achieved by only 28 players), is closely related to stable and superior technical performance, as these players outperformed their colleagues by 18% in overall performance. This analytical integration transforms mental observations into measurable and actionable data, enabling the coach to build predictive mental models and design precise interventions that meet the real needs of each player and the team.

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8.2. Tests of digital mental models

Quantitative results, Tables 4 and 5, demonstrate a strong statistical impact of the use of digital tests on measuring and improving mental models. The coefficients of influence (β) from the previous annexe confirm this:
Experience based on data (β = 0.45): the largest factor, reinforced by predictive tests that accelerate the construction of experience via simulation.
Instant feedback (β = 0.38): supported by digital self-awareness scales that provide the player with objective feedback on their mental performance.
Directed mental training (β = 0.41): now oriented based on the results of decision-making tests to address identified weaknesses with numbers.
Interactive video analysis (β = 0.33): converted from passive viewing into interactive tactical knowledge tests that measure assimilation.
To get the most out of them, these digital tests should be combined periodically (every 6–8 weeks) with technical data collection systems (e.g., Catapult). It is this dual measurement (technical + cognitive) that allows building dynamic digital mental models capable of predicting and developing a player's performance under various conditions, turning training into an accurate scientific process based on comprehensive data.

Table (4): Tests of digital mental models and measuring their effectiveness (the impact of improved mental models on actual performance indicators).

Mental model	Digital Measurement Instruments (Testing)	Statistical Results (Sample Average)	Interpreting the results and linking them to evolution
Tactical Model	**Computerized Tactical Knowledge Tests:** • Interactive video presentations with multiple-choice questions about game situations. • Simulated choosing the right position in a digital game map.	**Score: 95/100** (SD: ±4.2) **Response Time:** 2.1 seconds	A high score and low dispersion indicate **an excellent theoretical understanding** of the plans. The recorded development (+46%) reflects the success of AI video analysis in solidifying tactical concepts and turning them into measurable knowledge.
Cognitive Model	**Anticipation Tests:** • Display videos captured from the player's perspective that freeze at a critical moment, and ask to predict the path of the ball or the movement of a teammate/ opponent. • Use virtual reality glasses to measure the accuracy and speed of the prediction.	**Accuracy: 92%** (SD: ±5.1%) **Correct Prediction Time:** 0.35 seconds before the event	High accuracy (92%) and high sophistication (+42%) confirm that **quantitative data** from tracking systems (such as Catapult) helped players form **perceptual patterns** of competitors' movements, objectively improving their predictive ability.
Executive Model	**Tests of speed and quality of decision-making:** • Simulation games on touch screens that require the selection of a skill (passing, aiming, dribbling) within a specific time. • Measuring the accuracy of the selection against the time taken.	**Decision Time:** 0.40 sec (SD: ±0.08s) **Decision Accuracy:** 88%	High speed (0.40s) and accuracy (88%) explain the observed improvement in executive performance (+39%). Tests prove that **AI-based training** created a fast-recalling "mental kinetic library" in players.
Emotional Model	**Measures of self-awareness and emotional regulation:** •Physiological response measurements (heart rate, skin response) paired with simulated stressful situations. • Instantaneous post-scene digital questionnaires to measure self-esteem of the condition.	**Subjective-objective match:** 88% (match between player rating and device data) **Compression recovery time:** 35% improvement	A high match (88%) indicates the growth **of self-awareness**, which is the basis of emotional control. The evolution (+37%) in the emotional model is directly related to the **instantaneous feedback** programs from the AI data that helped the player understand their response under pressure.

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Table (5): Statistical conclusion and recommendation.

Practical Performance Indicator	Measured Improvement Rate	The Responsible Mind Model
Correct Throws	+60%	**Executive + Cognitive**
Defensive Coverage	+63%	**Tactical + Cognitive**
Quick Decisions	+67%	**Cognitive + Executive**
Collective Consensus	+62%	**Tactical + Emotional**

8.3. Presentation and discussion of results

Initial assumption: there are statistically significant differences at the level of significance ($\alpha \leq 0.05$) between the averages of the experimental and control groups in the tests of constructing mental models, in favor of the experimental group, Table 6.

Table (6): Testing the statistical differences between the experimental and control groups in the construction of mental models.

Dependent Variable Mental Model/Variable	Mean Dimensional Measurement of the Experimental Group (Mean ± SD)	Average telemetry of the control group (Mean ± SD)	Calculated value (t)	Impact size (Coh's d)
Tactical Model	94.2 ± 3.8	82.5 ± 6.1	12.35	**2.41 (Very Large Impact)**
Cognitive model (predictive accuracy)	91.5% ± 4.5%	79.8% ± 7.2%	10.87	**1.97 (Large Impact)**
Executive model (speed of decision-making)	0.39 sec ± 0.07	0.52 sec ± 0.10	-8.92	**1.52 (Large Impact)**
Emotional Model (Self-Awareness)	87.3% ± 5.1%	73.6% ± 8.4%	11.04	**1.94 (Large Impact)**
Overall score of mental models	90.8 ± 3.2	76.9 ± 5.9	16.18	**2.89 (Extra Large Impact)**

The statistical results obtained confirm the rejection of all null hypotheses (H0) and the acceptance of alternative hypotheses (H1) at a semantic level ($\alpha \leq 0.05$), which supports the existence of significant, statistically significant and practical differences between the experimental and control groups in the telemetry of all dimensions of mental models, in favor of the experimental group that used intervention supported by artificial intelligence techniques. Statistically speaking, the significance level (p-value) values of (0.000) for all tests indicate that the probability of such large differences between the two groups occurring randomly or due to chance is almost zero (less than 0.1%), which enhances the reliability and validity of the results (Field, 2018). In addition to the statistical significance, the large size of the effect (Cohen's d), which exceeded (0.8) in all variables, culminating in the tactical model (d=2.41) and the total score (d=2.89), confirms that these differences are not only of numerical significance, but have great practical Significance, where the effect size exceeding 2.0 indicates a tremendous effect of experimental intervention on dependent variables (Sawilowski, 2009).

The smaller standard deviation (SD) in the results of the experimental group compared to the control group (e.g. ±3.8 versus ±6.1 in the tactical test) reflects a higher degree of homogeneity in the response of the experimental subjects to the training program, which indicates the effectiveness of the AI methodology in providing more personalized and group-level interventions (Gonzalez et al., 2020).

From a scientific and cognitive point of view, these results can be explained by several theoretical frameworks. Social constructivism and Cognitive Load Theory explain this superiority, since immediate and objective feedback derived from artificial intelligence analyzes (such as videos with superimposed data from Catapult) helped to build more accurate and efficient mental representations of

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sports situations, which reduced the unnecessary cognitive load on players and enabled them to allocate their mental resources for tactical information processing and decision-making (sweller, 2011; Vygotsky, 1978).

The significant superiority in the tactical model (Mean=94.2) and predictive accuracy (91.5%) is attributed to the ability of AI-based simulation and analysis systems to provide diverse and repetitive training scenarios, which enhance learning based on Pattern Recognition and analytical Reasoning, which are the main pillars of tactical and cognitive competence in team sports (Gredin et al., 2020).

The improvement of the executive model (decision speed: 0.39 seconds) and the emotional model (self-awareness: 87.3%) are also explained by the theory of Self-Regulated Learning Theory. Quantitative performance data provided the player with an objective external criterion that enables him to compare his current performance with the target performance, which enhanced self-observation and self-Evaluation, two crucial stages in self-organization (Zimmerman, 2002).

Improving the speed of decision-making reflects the formation of more efficient neural pathways (Neural Pathways) through repetition supported by accurate feedback, which speeds up the process of information transition from the stage of perception to the stage of motor execution (Yarrow et al., 2009).

Accordingly, the integration of artificial intelligence into sports training not only develops cognitive skills but also re-engineers the basic mental processes of the player, which leads to significant and sustainable performance improvements.

The second assumption is that there is a statistically significant effect at a significance level ($\alpha \leq 0.05$) of a training program based on artificial intelligence and strategic planning technologies on improving the level of sports performance (such as shooting accuracy or defensive positioning) in handball players. See Table 6.

Table (6): Analysis of the statistical impact of an AI-based training program and strategic planning on sports performance.

Sport Performance Scale (Dependent Variable)	Percentage of improvement in the experimental group (post-previous)	Average improvement in the control group	Statistical test value (F or t)	Trace size (η^2 or Cohen's d)
Accurate aiming from advanced areas	+32.5% (58% to 90.5%)	+8.2% (59% to 67.2%)	F(1,118)= 185.42t= 13.61	η^2 = 0.61 d = 2.74 (very large effect)
Defensive positioning (correct coverage)	+28.7% (65% to 93.7%)	(66% to 72.5%) +6.5%	F(1,118)= 162.30t= 12.74	d = 2.53 (very large effect)η^2 = 0.58
Percentage of successful passes	+25.3% (71% to 96.3%)	+5.1% (72% to 77.1%)	F(1,118)= 149.85t= 12.24	d = 2.41 (very large effect)η^2 = 0.56
Speed of restoring offensive/defensive balance	+40.1% (time improvement from 2.5s to 1.5s)	+9.8% (2.5s to 2.25s)	F(1,118)= 210.50t= 14.51	η^2 = 0.64 d = 2.96 (very large effect)
Overall Performance Index (Composite Indicator)	+36.4%	+7.5%	F(1,118)= 245.67t= 15.67	η^2 = 0.68 d = 3.15 (very large effect)

Scientific and statistical interpretation of the results of the impact of the artificial intelligence and strategic planning program on sports performance. The statistical results presented in the table confirm the presence of a strong, statistically significant impact of the training program based on artificial intelligence and strategic planning technologies in improving all tested sports performance measures in handball players. The significance level (p-value) values of (0.000) for all comparisons indicate that the probability that such significant differences between the experimental and control groups occurred by chance is less than 0.1%, which strongly supports the alternative research hypothesis and rejects the null hypothesis (Field, 2018).

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The practical strength of this effect lies in the very large effect size, where Cohen's d values exceeded the barrier of 2.4 in all variables, reaching 3.15 in the overall performance index. According to Sawilowski's interpretation (Sawilowski, 2009), values above 2.0 are classified as representing a "huge" effect, which confirms that the differences created by the pilot program are not only statistically significant but also of great practical importance in the real mathematical field, where their effect can be clearly observed.

From a scientific point of view, this enormous improvement can be explained by the theoretical framework of the integration of technical and cognitive processing. Artificial intelligence technologies (such as biometric tracking systems and advanced video analysis) provide immediate and objective feedback (Gonzalez et al., 2020).

For instance, a 32.5% improvement in aiming accuracy is directly attributed to the ability of these technologies to analyze and process subtle variables such as the angle of the arm at launch, the point of departure of the ball, and the timing of the movement, and then provide measurable data to the coach and the player.

This quantitative information reduces the external cognitive load on the player, enabling him to concentrate his mental resources on the implementation of the skill instead of analyzing it (Sweller, 2011).

Subsequently, the role of strategic planning to turn this data into actionable knowledge. By building custom mental models for each player, the coach can design exercises that challenge specific weaknesses revealed by the data.

A significant improvement in the speed of restoring balance (+40.1%) is a direct product of this approach, as quick-response exercises based on real offensive and defensive patterns of competitors, pre-analyzed by artificial intelligence, are designed. This type of simulation and scenario-based training enhances implicit learning and the speed of information processing in the premotor cortex, thereby reducing reaction time (Gredin et al., 2020).

Moreover, the improvement in collective indicators such as successful passes (+25.3%) and defensive positioning (+28.7%) indicates that the program has successfully developed common mental models (shared mental models) within the team. When all players have a unified, data-based understanding of their roles and optimal movement spaces, coordination and non-verbal communication automatically improve (Eccles & Tran, 2012).

Finally, objective feedback promotes self-regulated learning, as the player becomes able to monitor and self-evaluate his performance based on standard criteria, which enhances his independence and motivation (Zimmerman, 2002).

9. Conclusions

Based on the analysis of the results from the current study, which was aimed at measuring the effectiveness of artificial intelligence and strategic planning techniques in building mental models to improve performance in handball, the following can be concluded:

1. The effectiveness of the techno-cognitive integration methodology: the results proved a strong and statistically significant effect of integrating artificial intelligence technologies (such as advanced video analytics for systems such as Catapult) with strategic planning in the development of mental models of players. This effect was not only statistical (all values of p-value = 0.000), but also practical and large in size (the size of the effect, Cohen's d, exceeded the barrier of 2.4 in all variables), which confirms the effectiveness of this integrative approach in the real mathematical field.

2. Holistic development of mental models: the pilot program improved all the components of the mental model in a superior way to traditional training. The experimental group showed significant superiority in the tactical model (average 94.2), the cognitive model (prediction accuracy 91.5%), the executive model (decision speed 0.39 seconds), and the emotional model (self-awareness 87.3%). This

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demonstrates that the technical-strategic intervention positively and comprehensively affects the cognitive structure of the player.

3. Direct translation of performance: improved mental models directly translated into tangible performance gains in the field. The experimental group showed a significant improvement in the accuracy of aiming (+32.5%), defensive positioning (+28.7%), the percentage of successful passes (+25.3%), and the speed of restoring balance (+40.1%). This proves a causal relationship between the development of mental processes and the improvement of executive outputs in the sport of handball.

4. The research team has confirmed the realization of the two main research hypotheses.

The experimental group showed statistically significant differences in all measures of mental models, supporting the hypothesis that AI-based interventions are preferable.

o the second assumption: it was confirmed that there is a statistically and practically significant effect of the pilot program on improving the basic sports performance indicators among handball players.

5. Comprehensive measurement system: The importance of dual measurement (technical assessment by artificial intelligence + cognitive assessment) has emerged as a necessary system for comprehensive understanding of performance. This combination has made it possible to explain complex phenomena (such as a decline in performance in the second half) by correlating physiological data with the psychological state, allowing more accurate and effective interventions.

Recommendations

In view of the conclusions reached, the study makes the following recommendations:

1. For coaches and sports academies:
   - adoption and popularization of AI tools: recommend the routine integration of advanced analysis programs (e.g., Catapult, Hudl) into training and evaluation processes, not only for data collection, but as a basis for tactical decision-making and planning of individual exercises.
   - Implementation of integrative training programs: designing and implementing strategic training plans that address in parallel the technical, physical, and mental aspects, with the use of artificial intelligence outputs to customize these programs according to the needs of each player.
   - Focus on structured mental training: introduce regular mental training sessions (e.g., mental visualization, decision-making exercises under stress, emotion management) as an integral part of the training curriculum, linking their results with quantitative performance data.
2. For sports institutions and federations:
   - Investment in technological infrastructure: allocate budgets to provide advanced hardware and software based on artificial intelligence to clubs and national teams, and provide the necessary technical support.
   - Human Resources Development: Holding specialized workshops and training courses for trainers and administrators on how to interpret artificial intelligence data and turn it into strategic plans and effective mental models.
   - creation of knowledge platforms: development of national or regional databases that collect and analyze the performance patterns of teams and players, enabling benchmarking and deriving evolutionary trends that help in long-term planning.
3. For researchers in the field of sports science:
   - Delve deeper into the study of neural and cognitive mechanisms: conduct further research using neuroimaging techniques (such as fMRI, EEG) to understand how AI-based feedback affects the formation of neural pathways and mental representations in the brains of athletes.
   - Longitudinal and comparative studies: carry out long-term studies to assess the sustainability of the impact of this methodology, make comparisons across different team sports (football, basketball, etc.) to identify general and adaptable elements of success.

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- Develop predictive models: work on building more sophisticated predictive algorithm models that use historical and cognitive data to predict players' performance under various scenarios or to identify promising talents based on multiple metrics.

4. Recommendations for the future:
   - Hyper-personalization: leveraging artificial intelligence to create a" digital twin " for each player, simulating their responses and predicting the results of different trainings, enabling the design of super-personalized training programs.
   - Integration of augmented and virtual reality (AR / VR): explore the use of advanced simulation techniques in virtual reality environments to train mental models in highly realistic, repeatable, and controllable game situations, without the risk of injuries associated with intensive field training.
   - Team knowledge management system: developing electronic systems that serve as a knowledge Center for the team, incorporating performance data, tactical plans, mental assessments, and video recordings, providing an integrated source of information for the coach and the players for reviewing performance and making decisions.

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