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Indoor Marksmanship Simulation Ranges for Military and Law-Enforcement Training: A Comprehensive Review of Technologies, Architectures, Artificial Intelligence and Emerging Trends

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Abstract
Marksmanship proficiency remains one of the most fundamental competencies required by military personnel, law-enforcement officers, and security operators. Effective weapons training directly influences mission success, force protection, combat effectiveness, and operational readiness. Traditionally, marksmanship training has relied on live-fire exercises conducted on outdoor and indoor firing ranges. While live-fire training provides realistic ballistic effects and authentic weapon handling experience, it is associated with significant challenges, including ammunition expenditure, safety risks, environmental concerns, range availability constraints, and limited opportunities for objective performance analytics. Advances in simulation technologies have led to the emergence of indoor marksmanship simulation systems capable of providing realistic, repeatable, cost-effective, and data-driven training environments. This paper presents a comprehensive review of indoor marksmanship simulation ranges and associated technologies employed in military and law-enforcement training. The review examines laser-based weapon simulators, infrared and optical tracking systems, high-speed camera-based hit detection architectures, pneumatic and electromechanical recoil simulators, computer vision-based scoring systems, Virtual Reality (VR), Augmented Reality (AR), mixed reality (MR), Artificial Intelligence (AI)-assisted coaching platforms, machine learning-based performance assessment systems, and digital twin technologies. Comparative analysis of commercial and military simulation systems is conducted, while current technological limitations, implementation challenges, and future research opportunities are critically evaluated. Particular emphasis is placed on the integration of computer vision, deep learning, Explainable AI (XAI), reinforcement learning, and adaptive training technologies for intelligent shooter performance optimisation. The review further identifies research gaps and proposes a technology roadmap for next-generation AI-enabled indoor marksmanship training ecosystems. The findings indicate that future military training systems will increasingly transition from score-based simulators toward autonomous, adaptive, and intelligent training platforms capable of continuously enhancing individual and collective combat readiness.

Keywords: *Indoor Marksmanship Simulator, Shooting Range Simulation, Military Training, AI, Computer Vision, Machine Learning, Digital Twin, Virtual Reality, Recoil Simulation, Human Performance Analytics.*

I. INTRODUCTION

Marksmanship remains a fundamental military and law-enforcement skill despite advances in Artificial Intelligence (AI), autonomous systems, and precision-guided weapons. The ability to accurately engage targets is critical to mission success in Close-Quarter Battle (CQB), urban warfare, counter-terrorism operations, and peace-support missions [1]–[4].

Traditionally, marksmanship training has relied on live-fire exercises, which provide realistic weapon-handling experience but are often constrained by ammunition costs, safety requirements, environmental concerns, and limited range availability [5]–[7]. To address these challenges, indoor marksmanship simulation ranges have emerged as effective training solutions that provide safe, cost-effective, and repeatable training environments. Modern systems integrate technologies such as laser emitters, optical and infrared sensors, high-speed cameras, computer vision, Virtual Reality (VR), Augmented Reality (AR), AI and digital twins to enable realistic weapon simulation, automated scoring, and objective performance assessment [8]–[12].

The evolution of indoor marksmanship training technologies is illustrated in Fig. 1. Early systems relied on mechanical target mechanisms and instructor observation, while subsequent generations introduced laser-based simulators, computer-based training platforms, and computer vision-enhanced systems. Current fifth-generation platforms incorporate Explainable AI (XAI), Reinforcement Learning (RL), Digital Twins, Human Performance Analytics, Edge AI, and Autonomous Coaching Systems, transforming conventional score-based simulators into intelligent and adaptive training ecosystems [13]–[18]. The growing adoption of indoor simulators is driven by reduced training costs, enhanced safety, all-weather availability, realistic scenario generation, and the ability to collect detailed performance data. Advances in computer vision, AI, high-speed imaging, VR/AR, and digital twin technologies now enable automated coaching, shooter tracking, posture assessment, trigger-control analysis, recoil monitoring, and personalised training recommendations [19]–[24].

Consequently, modern simulation systems employ a wide range of performance metrics beyond simple hit scores. As summarised in Table 1, these include accuracy, shot grouping, reaction time, aim stability, trigger control, recoil recovery, and composite shooter performance indices, enabling objective and data-driven assessment of marksmanship proficiency. Indoor marksmanship simulation systems may be classified according to tracking technology, recoil simulation mechanism, target presentation method, immersion level, and AI capability. The resulting technology taxonomy, shown in Fig. 2, encompasses laser-based, infrared, optical, high-speed camera, VR-, AR-, mixed-reality-, and AI-enabled training systems. This review provides a comprehensive assessment of indoor marksmanship simulation technologies for military and law-enforcement applications. It examines tracking and recoil simulation technologies, computer vision and AI-based performance assessment methods, VR/AR/MR and digital twin applications, and emerging trends shaping next-generation intelligent marksmanship training ecosystems.

2. Classification of Indoor Marksmanship Simulation Systems

Indoor marksmanship simulation systems employ a range of sensing, tracking, visualisation and performance-assessment technologies to replicate live-fire training within a safe, repeatable and cost-effective environment. Depending on the underlying technology, these systems differ in tracking accuracy, recoil realism, immersion level, training flexibility, and analytical capability. Consequently, a structured classification framework is essential for evaluating their suitability for military, law-enforcement, and civilian firearms training applications. As illustrated in Fig. 2, indoor marksmanship simulators may be categorised into eight major classes, namely laser-based systems, IR tracking systems, optical tracking systems, high-speed camera-based systems, VR, AR, Mixed Reality (MR) and AI-enabled intelligent training systems.

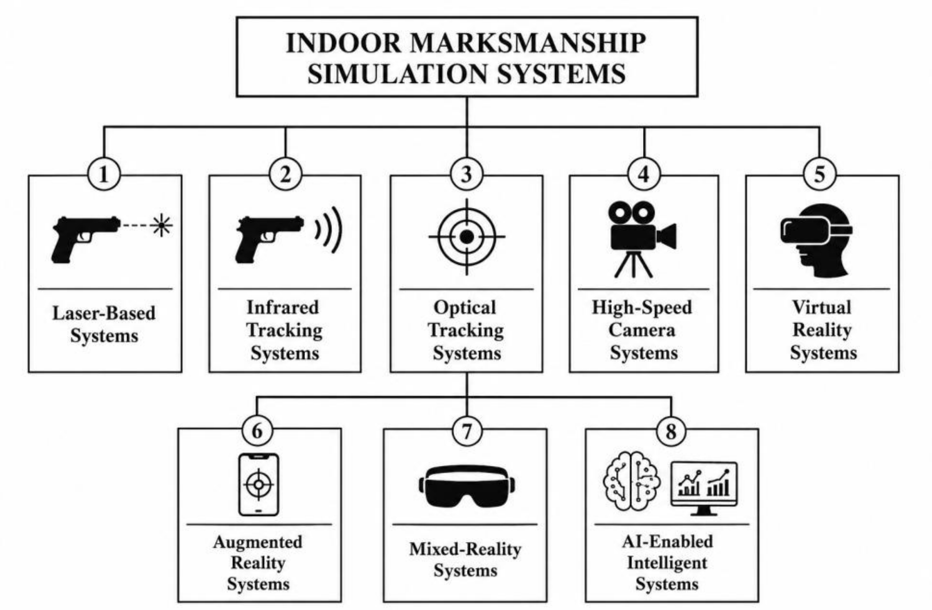

Fig. 2:. Classification of Indoor Marksmanship Simulation Systems

Laser-based and IR systems are widely adopted because of their relatively low cost, ease of deployment, and operational simplicity. Optical and high-speed camera systems provide enhanced shot localisation accuracy and detailed shooter-performance analytics. VR, AR and MR systems introduce immersive synthetic environments capable of replicating operational scenarios, while AI-enabled systems incorporate machine learning, adaptive coaching, automated assessment, and predictive performance analytics to improve training effectiveness [33]–[38].

Table 2: Classification of Indoor Marksmanship Simulation Systems

System Type	Primary Technology	Accuracy	Training Realism	Cost
Laser-Based	Laser emitters	Medium	Medium	Low
Infrared Tracking	IR sensors	Medium–High	Medium	Medium
Optical Tracking	Cameras and computer vision	High	High	Medium
High-Speed Camera	High-frame-rate imaging	Very High	High	High
VR Systems	Virtual environments	High	Very High	High
AR/MR Systems	Hybrid virtual-physical environments	High	Very High	High
AI-Enabled Systems	Multimodal sensor fusion and AI analytics	Very High	Very High	High

The classification presented in Fig. 2 and Table 2 provides a foundation for analysing the operating principles, performance characteristics, advantages and limitations of the various indoor marksmanship simulation technologies discussed in the subsequent sections.

3. Laser-Based and Optical Tracking Technologies

Laser-based and optical tracking technologies constitute the most widely deployed indoor marksmanship simulation solutions due to their affordability, safety, scalability and training effectiveness. These systems utilise laser emitters, optical sensors, cameras, and computer-vision algorithms to determine shot placement, monitor weapon movement, and assess shooter performance without the use of live ammunition [39]–[42]. A typical laser-based marksmanship simulator consists of a weapon simulator equipped with a laser emitter, a projection or target screen, an optical detection subsystem, a data-acquisition module, and performance-analysis software, as illustrated in Fig. 3.

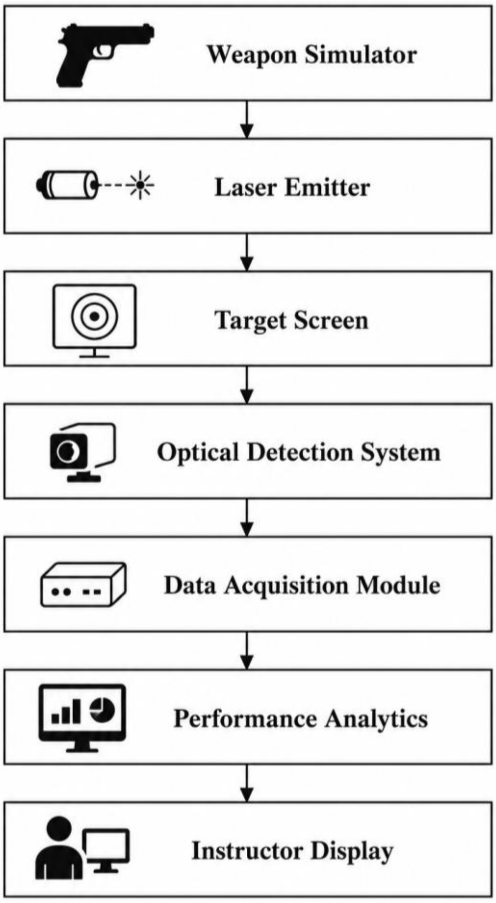

Fig. 3: Typical Architecture of a Laser-Based Marksmanship Simulator

3.1 Laser Spot Detection and Tracking

Laser-based systems determine shot impact positions by detecting the coordinates of the projected laser spot on the target plane. The impact position may be represented as:

$$P = (x, y) \qquad (1)$$

where x and y denote the horizontal and vertical coordinates of the detected impact point. The localisation error is given by:

$$E_p = \sqrt{(x - x_r)^2 + (y - y_r)^2} \qquad (2)$$

where x_r and y_r represent the reference target coordinates. Modern laser-based systems typically achieve sub-centimetre localisation accuracy under controlled indoor conditions [39], [40].

3.2 Optical Tracking Systems

Optical tracking systems employ cameras and machine-vision algorithms to continuously monitor weapon orientation, aiming behaviour, and shooter movement. Unlike conventional laser-only systems, optical tracking provides richer performance metrics including target acquisition speed, aim stability, trigger discipline and follow-through characteristics [33]–[36]. Tracking accuracy may be expressed as:

$$A_t = 1 - \frac{1}{N} \sum_{i=1}^{N} \frac{| p_i - \hat{p}_i |}{D_{\max}} \qquad (3)$$

where p_i and $\hat{p}_i$ represent the actual and estimated aiming positions, respectively, and $D_{\max}$ is the maximum allowable tracking deviation.

3.3 Aim Stability Assessment

Aim stability is a critical indicator of shooting proficiency and weapon-control effectiveness. It quantifies the shooter's ability to maintain a steady sight picture prior to trigger actuation. The Aim Stability Index (ASI) may be defined as:

$$S_a = 1 - \frac{\sigma_p}{P_{\max}} \qquad (4)$$

where σ_p is the standard deviation of muzzle movement and $P_{\max}$ is the maximum permissible displacement. Higher values indicate improved weapon steadiness and aiming consistency.

3.4 Shot Grouping Analysis

Shot grouping analysis evaluates shooting precision by measuring the spatial dispersion of impacts around the group centre. The grouping radius is expressed as:

$$R_g = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [(x_i - \bar{x})^2 + (y_i - \bar{y})^2]} \qquad (5)$$

where R_g denotes the shot-group radius and $(\bar{x}, \bar{y})$ represents the group centroid. Smaller values correspond to tighter shot groups and improved marksmanship performance.

3.5 Shooter Performance Assessment

Modern indoor simulators integrate multiple performance parameters into a composite metric known as the Shooter Performance Index (SPI), enabling objective trainee assessment and ranking:

$$SPI = w_1 A_s + w_2 S_a + w_3 R_t + w_4 F_t \qquad (6)$$

where A_s is the accuracy score, S_a is the aim stability index, R_t represents reaction time performance, F_t denotes follow-through performance, and w_i are weighting coefficients satisfying:

$$\sum_{i=1}^{4} w_i = 1 \qquad (7)$$

The SPI forms the foundation of many AI-assisted coaching and adaptive training systems [41]–[46].

Table 3: Typical Performance Metrics for Laser and Optical Tracking Systems

Metric	Description
Accuracy Score	Target hit ratio
Shot Grouping Radius	Precision of impacts
Reaction Time	Target engagement speed
Aim Stability Index	Weapon steadiness
Trigger Control Index	Trigger discipline
Follow-Through Score	Post-shot control
Recoil Recovery Time	Speed of target reacquisition
Shooter Performance Index	Composite performance metric

3.6 Advantages and Limitations

Laser-based and optical tracking systems offer significant advantages including low operating costs, enhanced safety, rapid deployment, minimal maintenance requirements, and real-time performance feedback. They enable extensive training repetitions without ammunition expenditure while providing quantitative performance metrics for both trainees and instructors. However, laser trajectories do not fully replicate external ballistic effects such as bullet drop, wind drift, projectile flight time, and terminal ballistics. In addition, optical tracking systems may experience performance degradation due to poor illumination conditions, sensor occlusion, image noise, and calibration errors [47]–[52]. Despite these limitations, ongoing advances in computer vision, machine learning, high-speed imaging, and sensor-fusion technologies continue to improve tracking precision, realism, and analytical capability, ensuring that laser-based and optical tracking systems remain central to modern indoor marksmanship training programmes.

4. Recoil Simulation Technologies

The effectiveness of an indoor marksmanship simulator depends not only on accurate shot localisation but also on its ability to reproduce the physical feedback associated with weapon discharge. Recoil significantly influences shooter posture, aim stability, trigger control, follow-through behaviour, and target reacquisition. Consequently, modern marksmanship simulators increasingly incorporate recoil-generation mechanisms to enhance training realism and improve skill transfer between simulated and live-fire environments [53]–[57]. As illustrated in Fig. 4, recoil simulation technologies may be broadly classified into four principal categories: pneumatic systems, electromechanical systems, gas-blowback systems, and hydraulic systems. Each technology offers distinct advantages in terms of recoil realism, implementation complexity, maintenance requirements, and operational cost.

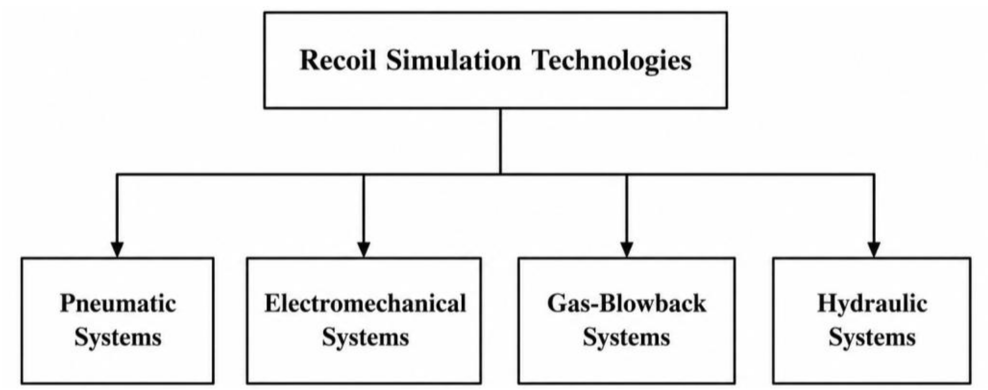

Fig. 4: Classification of Recoil Simulation Technologies

Pneumatic systems utilise compressed air to generate controlled recoil impulses and are widely employed in military and law-enforcement training simulators due to their robustness, reliability, and adjustable recoil characteristics. Electromechanical systems employ electric motors, solenoids, voice-coil actuators, or linear actuators to generate programmable recoil profiles. Gas-blowback systems use compressed gas cartridges to simulate weapon cycling and recoil effects, whereas hydraulic systems provide highly realistic recoil signatures suitable for specialised military training platforms [53], [58], [59]. The recoil impulse generated by a weapon may be expressed as:

$$I_r = \int_0^T F_r\,(t)dt \qquad (8)$$

where I_r is the recoil impulse (N·s), $F_r(t)$ is the recoil force as a function of time and T denotes the recoil duration.

A comparative assessment of recoil simulation technologies is presented in Table 4. As shown, hydraulic systems generally provide the highest recoil realism, while gas-blowback systems offer a low-cost solution with moderate fidelity. Pneumatic and electromechanical systems provide a practical compromise between realism, cost and maintainability.

Table 4: Comparison of Recoil Simulation Technologies

Technology	Recoil Realism	Cost	Complexity	Maintenance
Pneumatic	High	Medium	Medium	Medium
Electromechanical	High	Medium	Medium	Low
Gas-Blowback	Moderate	Low	Low	Medium
Hydraulic	Very High	High	High	High

To quantify simulator realism, the recoil fidelity index is defined by Eq. (9):

$$R_f = 1 - \frac{|\, I_r - I_s \,|}{I_r} \qquad (9)$$

where R_f denotes the recoil fidelity index, I_r represents the reference live-weapon recoil impulse, and I_s denotes the simulated recoil impulse. Values approaching unity indicate close agreement between the simulator and the actual weapon. Another important parameter is recoil energy, which characterises the kinetic effect experienced by the shooter:

$$E_r = \frac{1}{2} M_w V_r^2 \qquad (10)$$

where E_r is the recoil energy, M_w is the effective weapon mass, and V_r is the recoil velocity.

In addition to recoil fidelity, recoil recovery behaviour represents an important measure of shooter proficiency. The recoil recovery time is given by Eq. (11):

$$T_{rec} = t_{reacquire} - t_{fire} \qquad (11)$$

where t_{fire} denotes the firing instant and $t_{reacquire}$ represents the instant at which the shooter successfully reacquires the target. Lower values of T_{rec} indicate superior weapon control and follow-through performance [60].

Similarly, muzzle displacement after firing may be expressed as:

$$D_m = \sqrt{(x_f - x_0)^2 + (y_f - y_0)^2} \qquad (12)$$

where D_m represents muzzle displacement, while (x_0, y_0) and (x_f, y_f) denote the initial and final muzzle positions, respectively. A typical recoil simulation architecture is illustrated in Fig. 5.

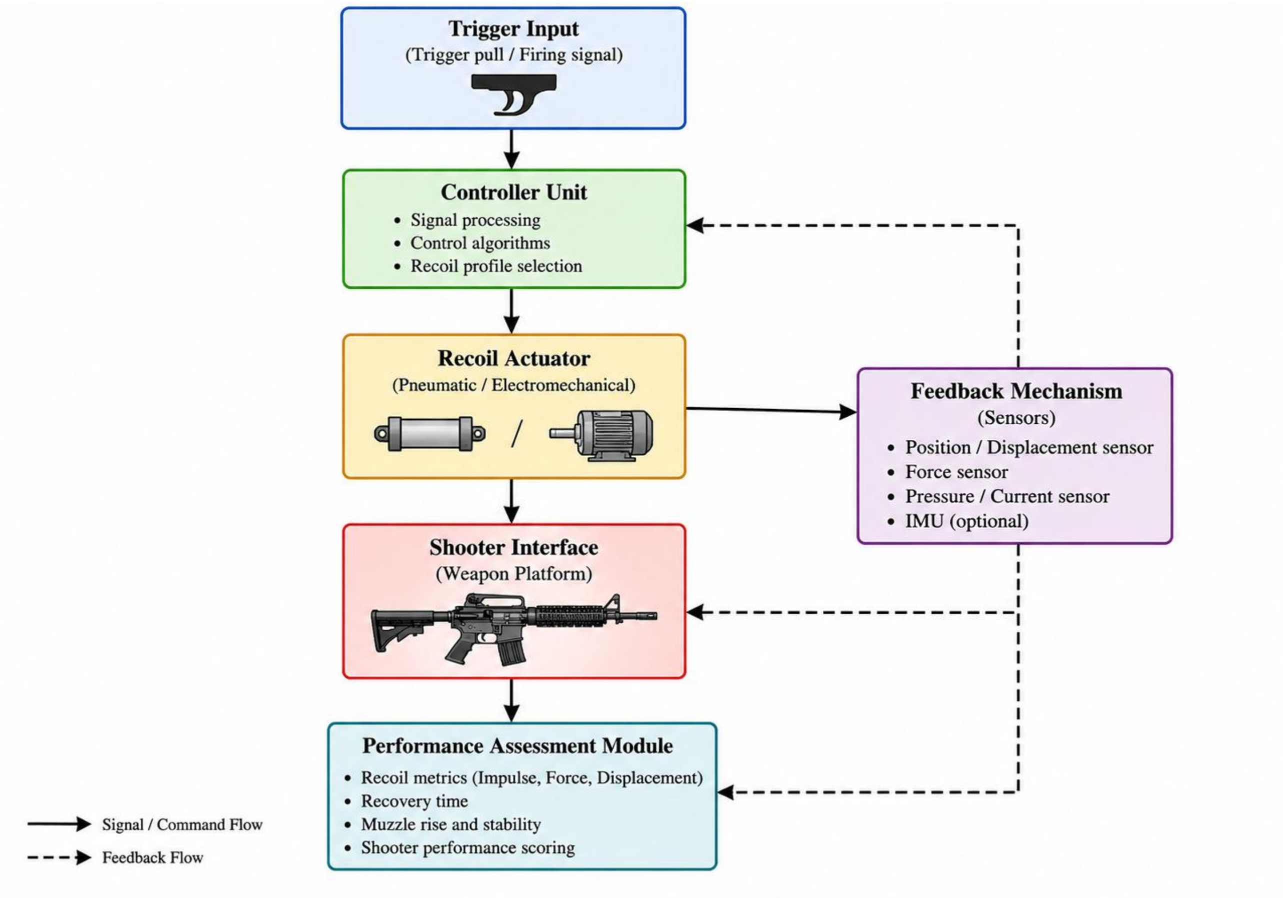

Fig. 5: Typical Architecture of a Recoil Simulation System

Upon trigger activation, the controller generates an appropriate recoil command that drives the actuator to reproduce the desired recoil profile. The feedback subsystem continuously monitors recoil performance and adapts system parameters to maintain realism. To objectively assess recoil performance, several evaluation metrics have been proposed in the literature. These metrics are summarised in Table 5.

Table 5: Representative Recoil Assessment Metrics

Metric	Description
Recoil Fidelity Index	Similarity to live-weapon recoil
Recovery Time	Time required to reacquire target
Muzzle Deviation	Weapon displacement following discharge
Follow-Through Score	Stability after trigger actuation
Recoil Consistency	Repeatability of recoil events

Despite substantial advances in recoil simulation technology, accurately reproducing weapon-specific recoil signatures, vibration spectra, bolt-carrier dynamics and shooter–weapon interaction effects remains a significant technical challenge. Emerging approaches based on adaptive control, sensor fusion, digital twins, and machine-learning-assisted recoil modelling are expected to further improve realism and training effectiveness in future indoor marksmanship simulators [54], [57], [61].

5. Computer Vision and High-Speed Camera-Based Systems

Recent advances in computer vision, AI and high-speed imaging have transformed indoor marksmanship simulators from simple shot-scoring platforms into intelligent performance-assessment systems capable of analysing shooter behaviour in real time. Modern systems continuously monitor weapon orientation, aiming behaviour, posture, trigger manipulation, reaction time, recoil response, and target engagement sequences using advanced imaging and machine-learning techniques [62]–[66]. A typical computer vision-based marksmanship assessment architecture is illustrated in Fig. 6.

Fig. 6: Computer Vision-Based Marksmanship Assessment Architecture

Computer vision systems utilise digital cameras and image-processing algorithms to identify, track and analyse both shooters and targets. These systems provide objective and repeatable measurements of marksmanship fundamentals that are often difficult to quantify through traditional instructor observation alone [63], [64]. High-speed imaging systems operating at frame rates ranging from several hundred to several thousand frames per second enable detailed analysis of transient shooting events such as trigger manipulation, muzzle displacement, recoil dynamics, and follow-through behaviour. The processing framework employed by such systems is illustrated in Fig. 7.

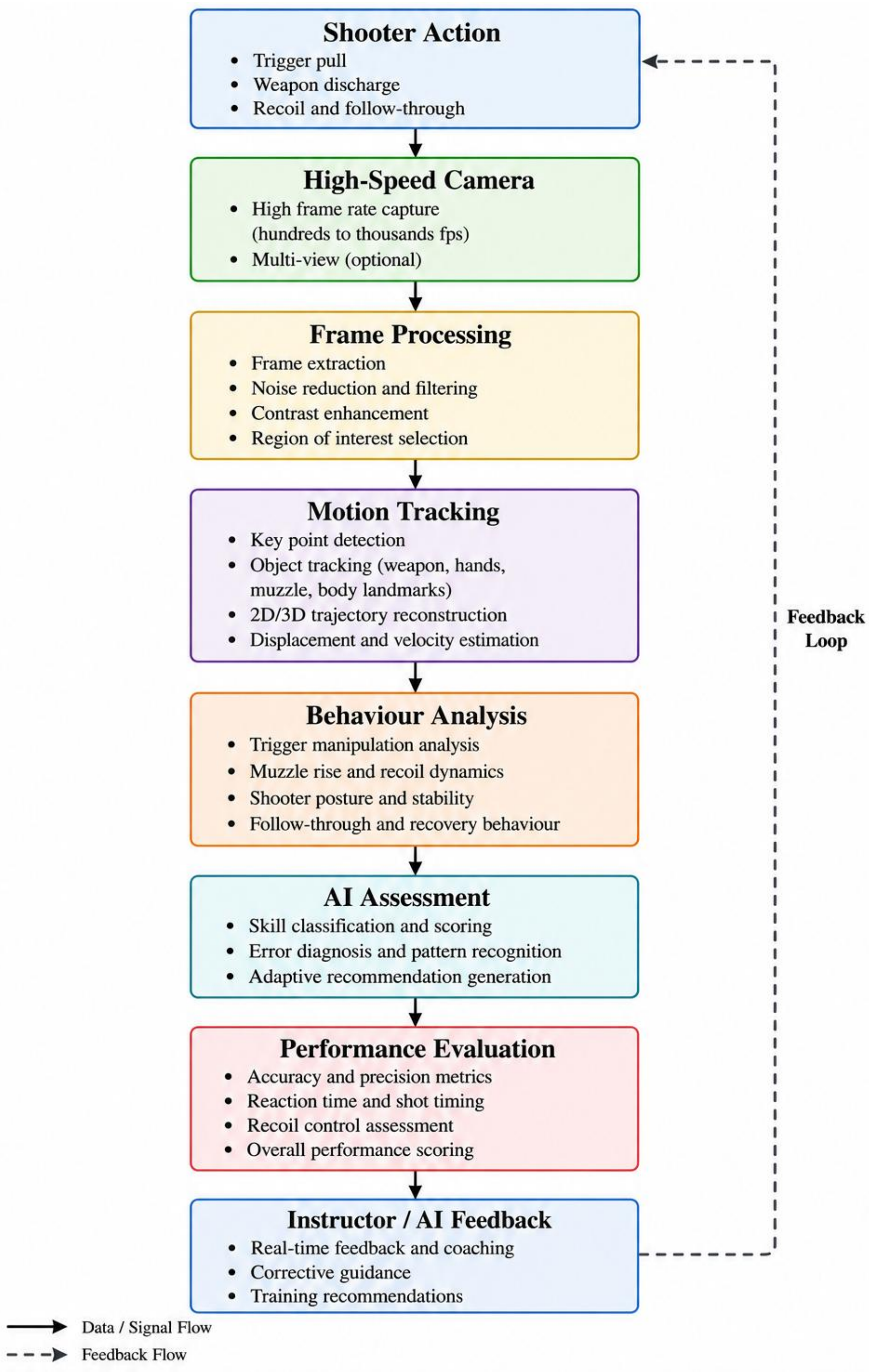

Fig. 7: High-Speed Camera-Based Shooter Analysis Framework

One of the most important performance indicators in computer vision-based systems is the probability of correctly detecting targets. This metric is defined by Eq. (13):

$$P_d = \frac{TP}{TP + FN} \tag{13}$$

where TP and FN denote the numbers of true-positive and false-negative detections, respectively. Target tracking accuracy can be quantified using Eq. (14):

$$A_t = 1 - \frac{1}{N}\sum_{i=1}^{N} \frac{|\,p_i - \hat{p}_i\,|}{D_{max}} \qquad (14)$$

where p_i and $\hat{p}_i$ represent the actual and estimated target positions, respectively and D_{max} denotes the maximum allowable tracking deviation.

Human-pose estimation algorithms are frequently employed to assess shooting posture and body alignment. The root-mean-square pose-estimation error is expressed by Eq. (15):

$$E_p = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |\,J_i - \hat{J}_i\,|^2} \qquad (15)$$

where J_i and $\hat{J}_i$ denote the actual and estimated body-joint coordinates, respectively. For deep-learning-based target detection systems, the classification loss may be represented by the cross-entropy loss function:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \qquad (16)$$

where C denotes the number of classes, y_i is the true label, and $\hat{y}_i$ is the predicted probability. To support comprehensive shooter evaluation, multiple performance indicators may be integrated into a unified SPI (Equ 6). The weighting coefficients satisfy:

$$\sum_{i=1}^{4} w_i = 1 \qquad (17)$$

The principal computer vision tasks employed in marksmanship assessment are summarised in Table 6.

Table 6: Computer Vision Tasks in Marksmanship Assessment

Task	Application
Target Detection	Target identification and localisation
Weapon Tracking	Aim-point monitoring
Pose Estimation	Shooter-posture assessment
Motion Analysis	Trigger and recoil evaluation
Behaviour Recognition	Skill assessment
Performance Prediction	Adaptive coaching and training optimisation

A comparison between conventional imaging systems and high-speed camera systems is presented in Table 7.

Table 7: Comparison of Imaging Technologies

Parameter	Conventional Camera	High-Speed Camera
Frame Rate	30–60 fps	500–5000 fps
Motion Blur	High	Very Low
Trigger Analysis	Limited	Excellent
Recoil Analysis	Limited	Excellent
Behaviour Analytics	Moderate	Very High

As shown in Table 7, high-speed cameras significantly improve trigger analysis, recoil assessment and behavioural analytics by reducing motion blur and capturing rapid weapon dynamics with high temporal resolution. The integration of computer vision, deep learning, pose estimation, high-speed imaging, and AI-assisted coaching is expected to play a central role in next-generation intelligent marksmanship training systems. These technologies enable objective performance measurement, automated coaching, adaptive training, predictive skill assessment, and personalised learning, thereby enhancing training effectiveness, marksmanship proficiency, and operational readiness [69]–[80].

6. Virtual Reality, Augmented Reality, and Mixed Reality Systems

The continuous advancement of immersive technologies has significantly transformed modern military training methodologies. The adoption of VR, AR, and MR technologies in military and law-enforcement training has accelerated significantly in recent years due to their ability to provide immersive, repeatable and cost-effective training environments [81]–[90], [124]. VR, AR and MR systems are increasingly integrated into indoor marksmanship simulators to provide realistic, interactive, and adaptive training environments. These technologies enable trainees to engage in tactical scenarios such as urban warfare, room-clearing operations, convoy protection, hostage rescue, and close-quarter battle exercises within safe and controlled environments while maintaining high levels of realism [81]–[90], [125]. Unlike conventional laser-based simulators that primarily focus on shot placement and weapon handling, immersive technologies provide a comprehensive training ecosystem that combines realistic visualisation, weapon interaction, environmental awareness, cognitive workload assessment, and tactical decision-making. As illustrated in Fig. 8, immersive marksmanship technologies may be categorised into VR, AR, and MR systems.

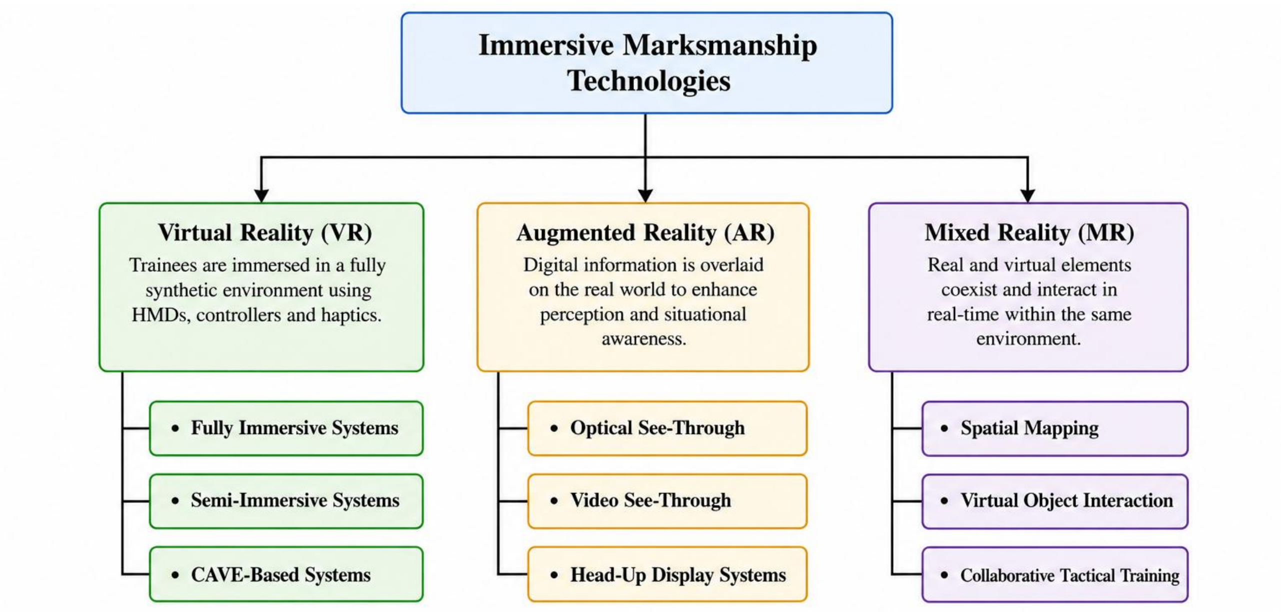

Fig. 8: Classification of Immersive Marksmanship Training Technologies

VR systems immerse trainees within completely synthetic environments generated using advanced rendering engines and simulation software. Users typically interact with the virtual environment through Head-Mounted Displays (HMDs), motion controllers, weapon-tracking systems, and haptic devices [83], [84]. AR systems overlay digital information, tactical cues, virtual targets, and battlefield intelligence onto real-world environments. These systems enable trainees to maintain situational awareness while receiving enhanced visual information during training exercises [82], [87]. MR systems combine elements of both VR and AR by allowing virtual objects to interact dynamically with physical environments. This capability enables realistic engagement with virtual adversaries, obstacles, and mission objectives within actual training facilities [85], [88]. A typical immersive marksmanship training architecture is illustrated in Fig. 9.

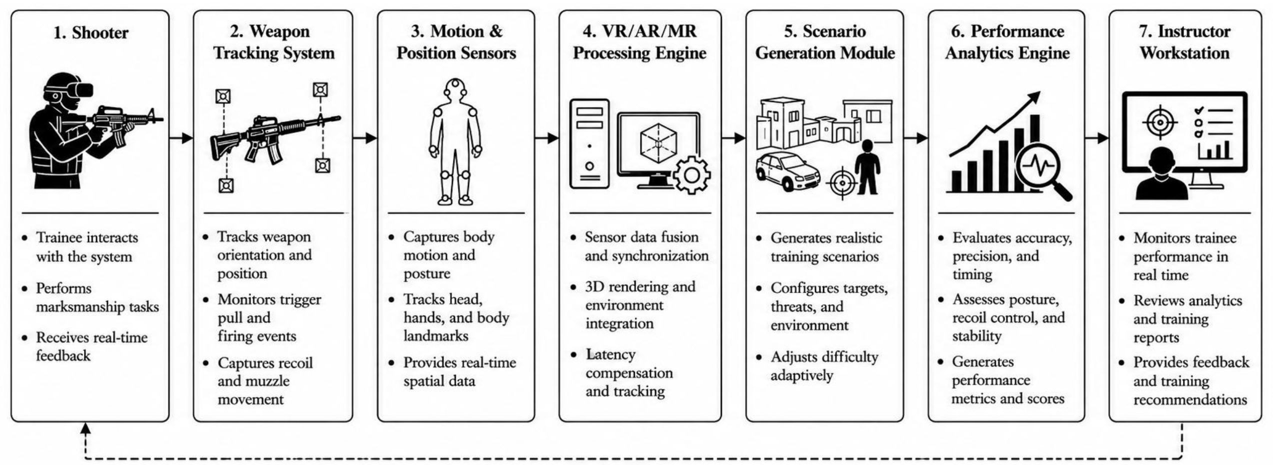

Fig. 9: Typical VR/AR/MR Marksmanship Training Architecture

The quality of immersion may be quantified using an Immersion Index (II) defined by Eq. (18):

$$II = w_1 FOV + w_2 R + w_3 I + w_4 L \qquad (18)$$

where FOV denotes field of view, Rrepresents display resolution, I is the interactivity score, L denotes latency performance, and w_1–w_4 are weighting coefficients satisfying Eq. 19:

$$\sum_{i=1}^{4} w_i = 1 \qquad (19)$$

Motion-to-photon latency is one of the most important performance metrics in immersive systems and may be expressed as

$$T_{MTP} = T_{track} + T_{render} + T_{display} \qquad (20)$$

where T_{track}, T_{render}, and $T_{display}$denote tracking delay, rendering delay, and display latency, respectively. Lower values of T_{MTP}improve realism and reduce simulator sickness [83], [84].

The effectiveness of immersive training may be evaluated using the Training Transfer Ratio (TTR):

$$TTR = \frac{P_{live}}{P_{sim}} \qquad (21)$$

where $P_{live}$and P_{sim}represent live-fire and simulator performance scores, respectively. Values approaching unity indicate strong transfer of skills from simulated environments to real-world marksmanship performance. The principal characteristics of immersive technologies are summarised in Table 8.

Table 8: Comparison of Immersive Marksmanship Technologies

Parameter	VR	AR	MR
Immersion Level	Very High	Moderate	High
Situational Awareness	Low	High	High
Real Environment Visibility	No	Yes	Yes
Tactical Realism	High	Moderate	Very High
Hardware Complexity	Medium	Medium	High
Cost	Medium	Medium	High

The principal evaluation metrics employed in immersive training systems are presented in Table 9.

Table 9: Performance Metrics for VR/AR/MR Systems

Metric	Description
Immersion Index	Degree of environmental immersion
Motion-to-Photon Latency	System responsiveness
Training Transfer Ratio	Skill-transfer effectiveness
Scenario Realism Score	Environmental fidelity
Tactical Decision Score	Decision-making performance
Situational Awareness Index	Environmental perception

Recent advances in immersive technologies have enabled the integration of eye-tracking systems, physiological monitoring sensors, haptic feedback devices, and AI-generated tactical scenarios. Future systems are expected to incorporate digital twins, collaborative multi-user environments, adaptive mission generation, and cloud-based simulation architectures capable of supporting large-scale distributed military training exercises [81], [88]–[90], [125]. More so, recent systematic reviews have reported significant improvements in learner engagement, skill acquisition, and situational awareness when immersive technologies are integrated into training programmes [124]. Future immersive training environments are expected to integrate digital twins, industrial metaverse concepts, physiological monitoring, and AI-driven analytics within unified training ecosystems [123].

7. AI and ML in Marksmanship Training

AI and ML technologies are increasingly transforming indoor marksmanship simulators from passive scoring systems into intelligent training platforms capable of adaptive coaching, behavioural analysis, performance prediction and autonomous assessment. AI-enabled systems continuously analyse large volumes of visual, inertial, physiological, and weapon-performance data to provide personalised feedback and optimise training outcomes [91]–[110]. Unlike traditional simulators that rely on predefined scoring metrics, AI-driven systems identify hidden patterns in shooter behaviour, detect performance deficiencies, predict future proficiency levels, and recommend corrective actions tailored to individual trainees. The overall architecture of an AI-enabled marksmanship training system is illustrated in Fig. 10.

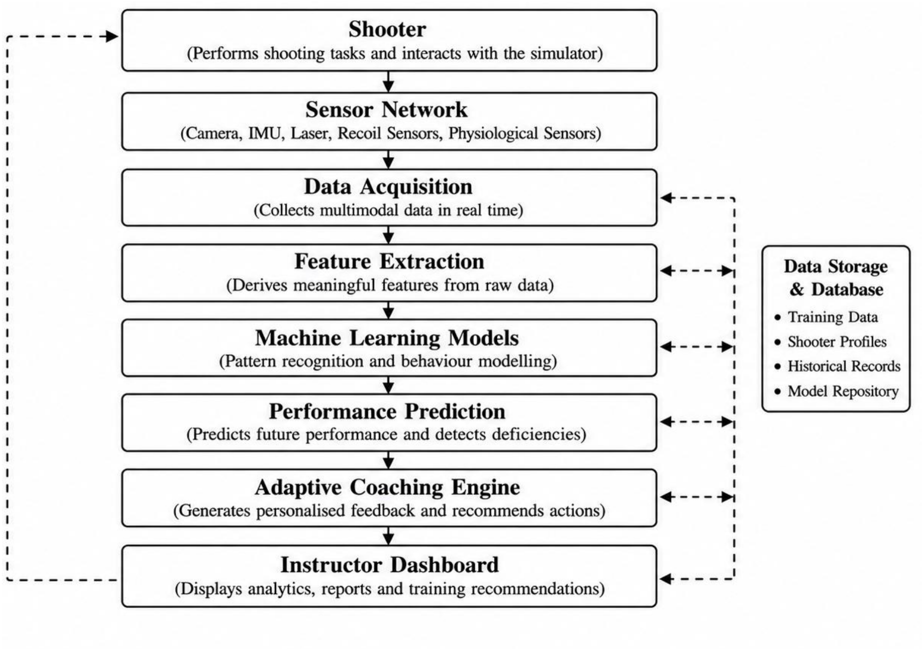

Fig. 10: AI-Based Marksmanship Training Framework

ML algorithms commonly employed in marksmanship assessment include Decision Trees, Random Forests, Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer architectures [91]–[104]. The prediction accuracy of an AI-based assessment model may be expressed as:

$$A_p = \frac{N_c}{N_t} \qquad (22)$$

where N_c represents the number of correctly predicted outcomes and N_t denotes the total number of observations.

For classification-based performance assessment, precision and recall are defined by Eqs. (23) and (24), respectively:

$$Precision = \frac{TP}{TP + FP} \qquad (23)$$

$$Recall = \frac{TP}{TP + FN} \qquad (24)$$

where TP, FP, and FNdenote true-positive, false-positive, and false-negative classifications, respectively.

The F1-score, widely employed for evaluating machine-learning classifiers, is given by:

$$F1 = \frac{2(Precision)(Recall)}{Precision + Recall} \qquad (25)$$

For adaptive coaching applications, a Shooter Skill Score (SSS) may be formulated as:

$$SSS = w_1 A + w_2 S + w_3 R + w_4 C \qquad (26)$$

where: A= shooting accuracy score, S= aim stability score, R= reaction-time score and C= shooting consistency score. The weighting coefficients satisfy:

$$\sum_{i=1}^{4} w_i = 1 \qquad (27)$$

Deep-learning-based vision systems frequently employ cross-entropy loss functions during training:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \qquad (28)$$

where y_i and $\hat{y}_i$ represent actual and predicted class probabilities, respectively. The ML training pipeline employed in intelligent marksmanship systems is illustrated in Fig. 11.

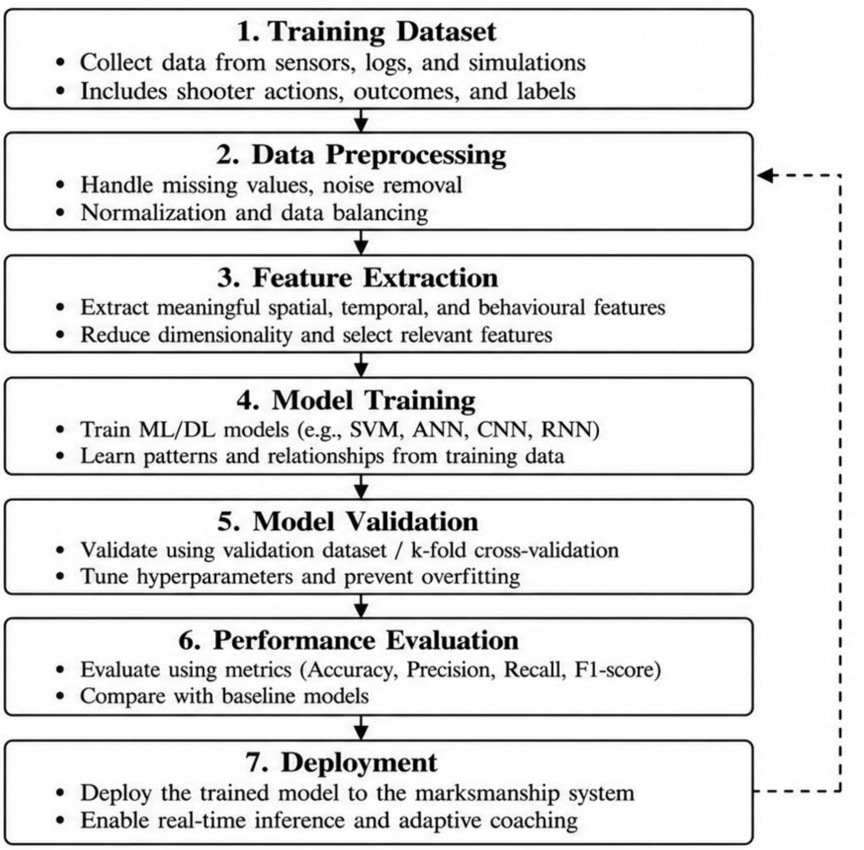

Fig. 11: Machine Learning Training Pipeline.

The principal AI and ML techniques employed in marksmanship simulators are summarised in Table 10.

Table 10: AI/ML Techniques for Marksmanship Assessment

Technique	Application
Decision Trees	Shooter classification
Random Forests	Performance prediction
Support Vector Machines	Behaviour recognition
CNNs	Target detection and posture analysis
RNNs	Sequential shooting analysis
Transformers	Behaviour modelling and prediction
Reinforcement Learning	Adaptive coaching

Performance benefits of AI-assisted training systems are summarised in Table 11.

Table 11: Benefits of AI-Driven Marksmanship Training

Benefit	Description
Automated Assessment	Objective performance evaluation
Adaptive Coaching	Personalised training recommendations
Skill Prediction	Forecasting trainee progression
Behaviour Analysis	Identification of shooting deficiencies
Reduced Instructor Workload	Automated feedback generation
Continuous Learning	Model improvement over time

Recent advances in computer vision have enabled AI systems to analyse shooter posture, weapon orientation, trigger manipulation, recoil behaviour, target engagement sequences, and eye movement patterns. Human pose-estimation algorithms such as OpenPose and Stacked Hourglass Networks have demonstrated significant capability in assessing shooting posture and movement quality [101], [102]. Transformer architectures originally introduced by Vaswani et al. [97] have further enhanced behavioural modelling capabilities by enabling long-range temporal analysis of shooting sequences and tactical actions. Reinforcement-learning techniques have also been investigated for adaptive coaching systems capable of generating personalised training programmes based on individual performance trends [96]. Future intelligent marksmanship simulators are expected to integrate multimodal sensor fusion, XAI, federated learning, digital twins, physiological monitoring, and Large Language Model (LLM)-based coaching assistants. The convergence of AI and digital-twin technologies is enabling intelligent training ecosystems capable of predictive performance assessment, adaptive scenario generation, and autonomous coaching [122]. Such technologies will enable highly personalised, adaptive, and data-driven training environments capable of continuously optimising shooter performance while enhancing operational readiness, combat effectiveness, and training efficiency.

8. Human Factors and Training Effectiveness

Human factors play a critical role in determining the effectiveness of marksmanship training systems. Regardless of the sophistication of the simulator technology employed, training outcomes ultimately depend on how effectively the system enhances human performance, skill acquisition, decision-making, situational awareness, cognitive processing, and behavioural adaptation. Consequently, modern indoor marksmanship simulators increasingly incorporate principles from human factors engineering, cognitive psychology, ergonomics, and learning sciences to maximise training effectiveness [111]–[120]. Human factors in marksmanship training encompass physical, cognitive, perceptual and psychological elements that influence shooter performance. These factors include posture, visual perception, attention allocation, reaction time, workload, fatigue, stress, situational awareness, and decision-making capability. As illustrated in Fig. 12, human performance in marksmanship training is influenced by multiple interacting factors.

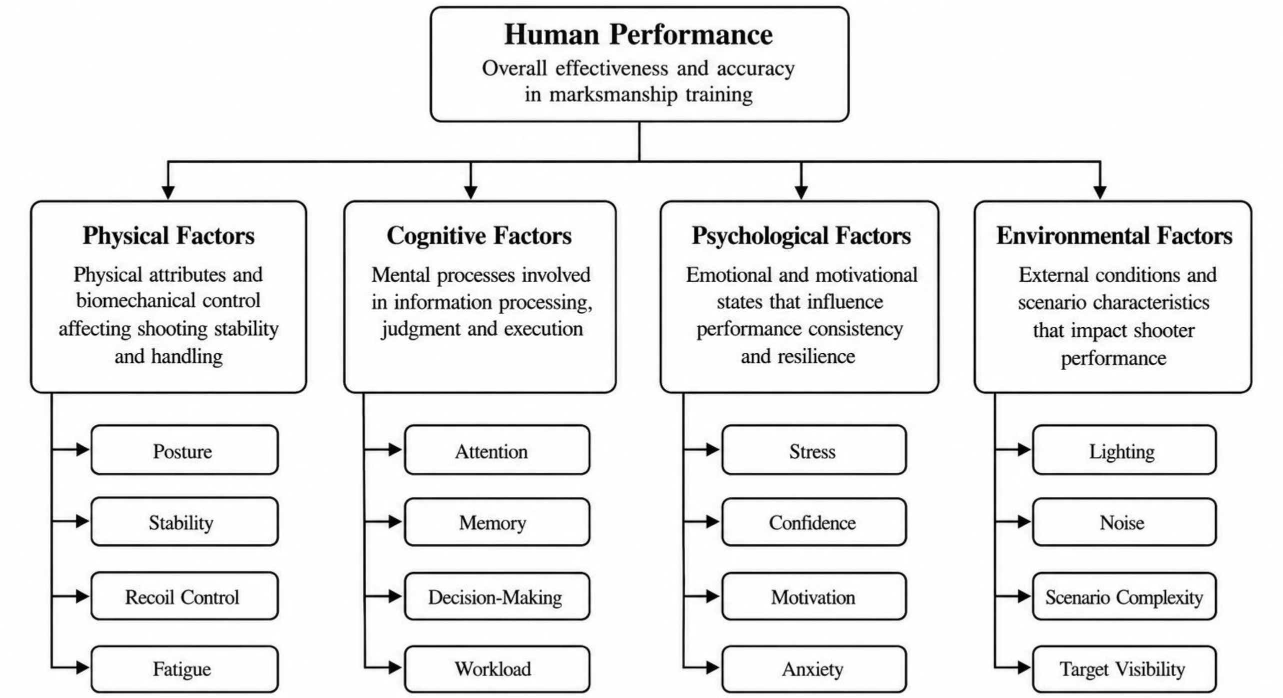

Fig. 12: Human Factors Influencing Marksmanship Performance.

A fundamental objective of military marksmanship training is to facilitate skill acquisition and retention. Training effectiveness is commonly evaluated by measuring improvements in performance before and after training interventions. The Training Effectiveness Index (TEI) may be expressed as:

$$TEI = \frac{P_{post} - P_{pre}}{P_{pre}} \qquad (29)$$

where P_{pre} and P_{post} denote pre-training and post-training performance scores, respectively.

Situational awareness is widely recognised as a critical determinant of combat effectiveness and marksmanship performance. According to the three-level situational awareness model proposed by Mica Endsley, situational awareness comprises the perception of environmental elements, comprehension of their meaning, and projection of their future status [111]. In marksmanship training, these capabilities enable shooters to detect threats, interpret tactical cues, and anticipate target behaviour under dynamic operational conditions. A Situational Awareness Index (SAI) may be expressed as:

$$SAI = w_1P + w_2C + w_3Pr \qquad (30)$$

where Pdenotes the perception score, Crepresents the comprehension score, Prdenotes the projection score, and w_1, w_2, and $w_3$are weighting coefficients satisfying:

$$\sum_{i=1}^{3} w_i = 1 \qquad (31)$$

Higher values of the SAI indicate enhanced awareness of the operational environment and are generally associated with improved target engagement effectiveness and decision-making performance.

Cognitive workload is another important human-performance factor that directly influences marksmanship outcomes. Excessive workload can degrade target detection, slow reaction times, impair decision-making, and reduce weapon-control effectiveness. One of the most widely adopted workload assessment tools is the NASA Task Load Index (NASA-TLX), which evaluates workload across six dimensions: mental demand, physical demand, temporal demand, effort, frustration, and perceived performance [112]. The overall workload score may be approximated as:

$$WL = \frac{1}{6}\sum_{i=1}^{6} D_i \qquad (32)$$

where $D_i$represents the score of the i^{th}workload dimension. Higher values of WLindicate increased cognitive and physical workload imposed on the shooter.

By combining situational awareness measures, workload assessments, behavioural analytics, and marksmanship performance metrics, modern indoor simulation systems can provide a comprehensive evaluation of human performance. Such assessments enable instructors to identify performance limitations, optimise training programmes, and develop adaptive coaching strategies tailored to individual trainees. A typical framework for evaluating human performance in marksmanship training is illustrated in **Fig. 13**.

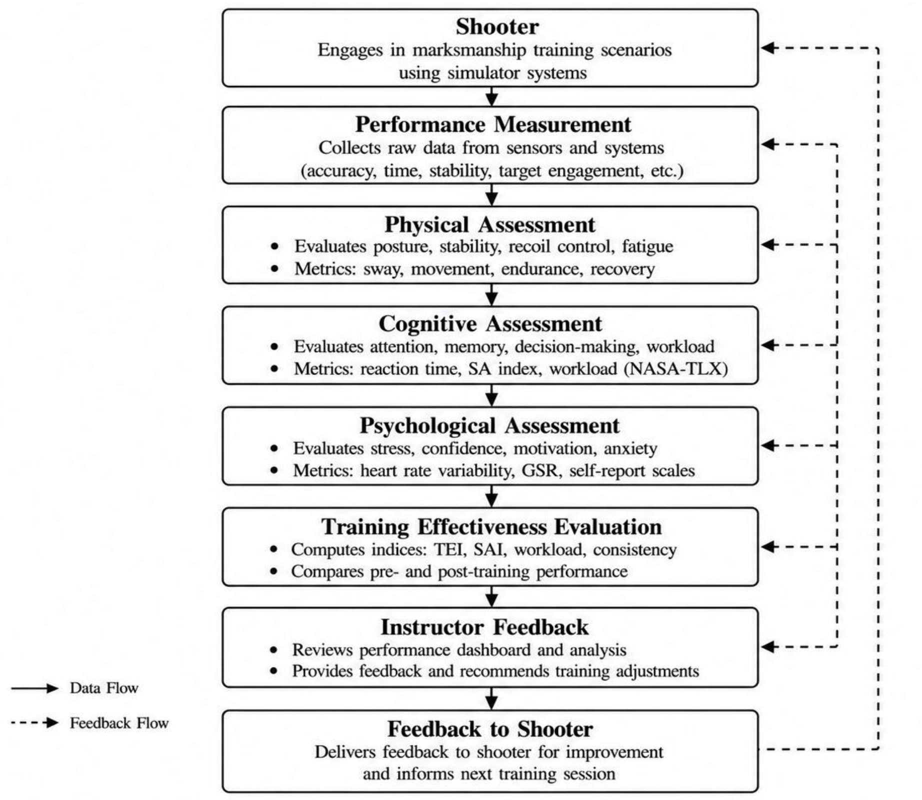

Fig. 13: Human Performance Assessment Framework

Several performance indicators are employed to assess training effectiveness. These metrics are summarised in Table 12.

Table 12: Human Factors Performance Metrics

Metric	Description
Accuracy Score	Target-hit performance
Reaction Time	Target engagement speed
Situational Awareness	Environmental understanding
Workload Index	Cognitive workload level
Skill Retention	Long-term learning effectiveness
Stress Level	Psychological response
Decision Accuracy	Tactical judgement performance

Human factors research has consistently demonstrated that immersive training systems improve trainee engagement, motivation, skill acquisition, and knowledge retention when compared with conventional instructional approaches. However, factors such as excessive visual complexity, simulator sickness, unrealistic feedback, and cognitive overload can adversely affect learning outcomes and reduce training effectiveness [113]–[116]. Training transfer is widely regarded as one of the most important indicators of simulator effectiveness because it measures the extent to which skills acquired in a simulated environment translate to live-fire performance. The transfer effectiveness of a simulator may be quantified using the Transfer Effectiveness Ratio (TER):

$$TER = \frac{L_{sim}}{L_{live}} \qquad (33)$$

where L_{sim} denotes the learning achieved through simulator-based training and L_{live} represents the learning achieved through live-fire training. Values approaching unity indicate that simulator-based instruction effectively replicates the learning outcomes obtained during live-fire exercises. Several factors influence the effectiveness of training transfer between simulated and operational environments. As summarised in Table 13, recoil realism, visual fidelity, scenario realism, instructor feedback, immersion level, cognitive load, and training frequency all contribute to the degree of skill transfer achieved. Among these factors, recoil realism, visual fidelity, scenario realism, instructor feedback, and training frequency have been identified as having particularly strong influences on marksmanship skill acquisition and retention.

Table 13: Factors Affecting Training Transfer

Factor	Influence on Transfer
Recoil Realism	High
Visual Fidelity	High
Scenario Realism	High
Instructor Feedback	High
Immersion Level	Moderate–High
Cognitive Load	Moderate
Training Frequency	High

Recent studies indicate that adaptive training systems, AI-assisted coaching, physiological monitoring, and immersive simulation environments can significantly improve skill acquisition and retention while reducing training costs and safety risks [117]–[120].

9. Comparative Assessment of Commercial Systems

The rapid evolution of sensing, simulation, AI and immersive technologies has resulted in the development of numerous commercial marksmanship training systems for military, law-enforcement, and civilian applications. These systems employ different combinations of laser tracking, optical sensing, computer vision, recoil simulation, virtual environments, and AI-based performance analytics to provide safe, repeatable, and cost-effective training solutions. Consequently, a comparative assessment of representative commercial systems provides valuable insight into the current state of the technology, prevailing design trends, and future directions for intelligent marksmanship training systems.

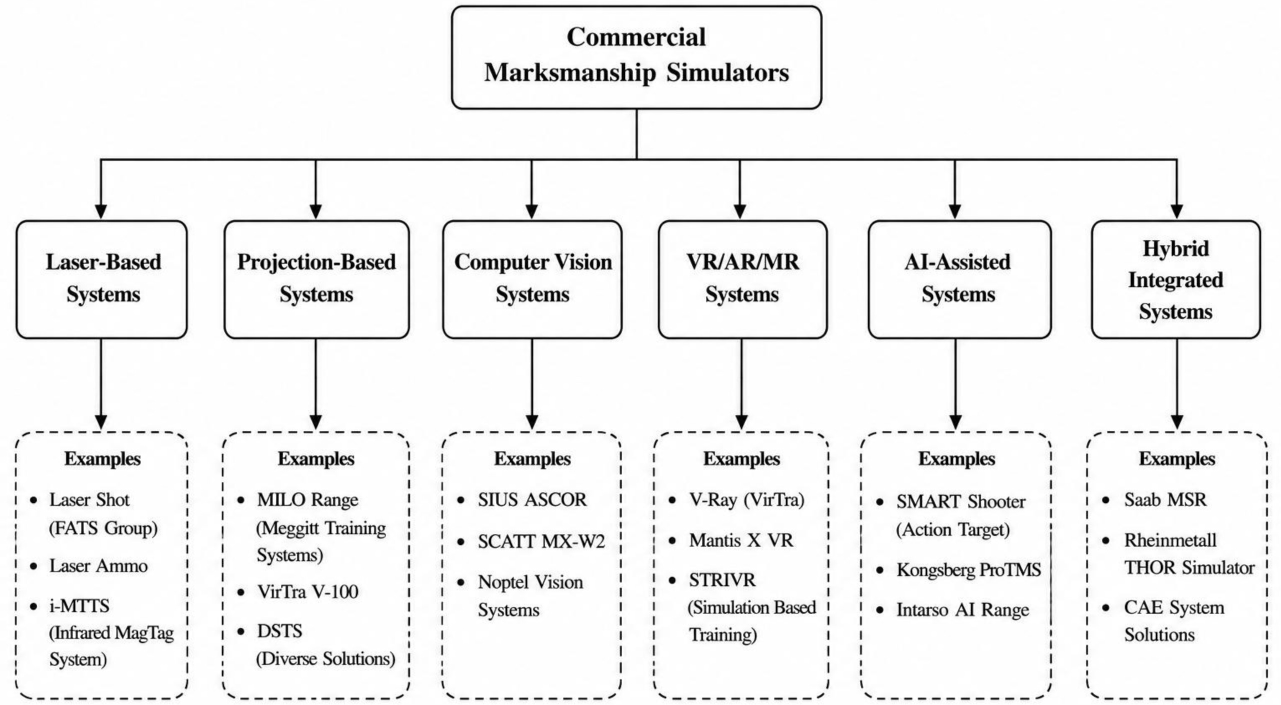

Fig. 14: Classification of Commercial Marksmanship Simulation Systems.

As illustrated in Fig. 14, contemporary commercial marksmanship simulators may be broadly classified into six major categories: laser-based systems, projection-based systems, computer vision systems, VR/AR/MR systems, AI-assisted systems, and hybrid integrated systems. Each category offers distinct advantages in terms of realism, deployment requirements, scalability, training fidelity, and analytical capability.

Representative commercial systems and their enabling technologies are summarised in Table 14. Laser-based systems such as Laser Shot and Laser Ammo emphasise affordability and ease of deployment, whereas projection-based platforms such as MILO Range and VirTra provide immersive scenario-based training. Computer-vision systems, including SCATT MX-W2 and SIUS ASCOR, focus on precision performance measurement and shooter analytics. More recent platforms integrate virtual reality, artificial intelligence, and multi-sensor fusion technologies to provide adaptive coaching, predictive assessment, and enhanced situational awareness training.

Table 14: Classification of Representative Commercial Systems

Category	Representative Systems	Key Technologies
Laser-Based	Laser Shot, Laser Ammo	Laser emitters, optical sensors
Projection-Based	MILO Range, VirTra	Projection screens, scenario generation
Computer Vision	SCATT MX-W2, SIUS ASCOR	Cameras, image processing
VR/AR/MR	VirTra V-Ray, Mantis X VR	HMDs, immersive environments
AI-Assisted	SMART Shooter, ProTMS	Machine learning, adaptive coaching
Hybrid Integrated	Saab MSR, Rheinmetall simulators	Multi-sensor fusion, AI, VR

Although the underlying technologies differ, most modern systems follow a common functional architecture comprising a weapon simulator, tracking subsystem, scenario-generation engine, performance analytics module, instructor station, and after-action review capability. This generalised architecture is illustrated in Fig. 15.

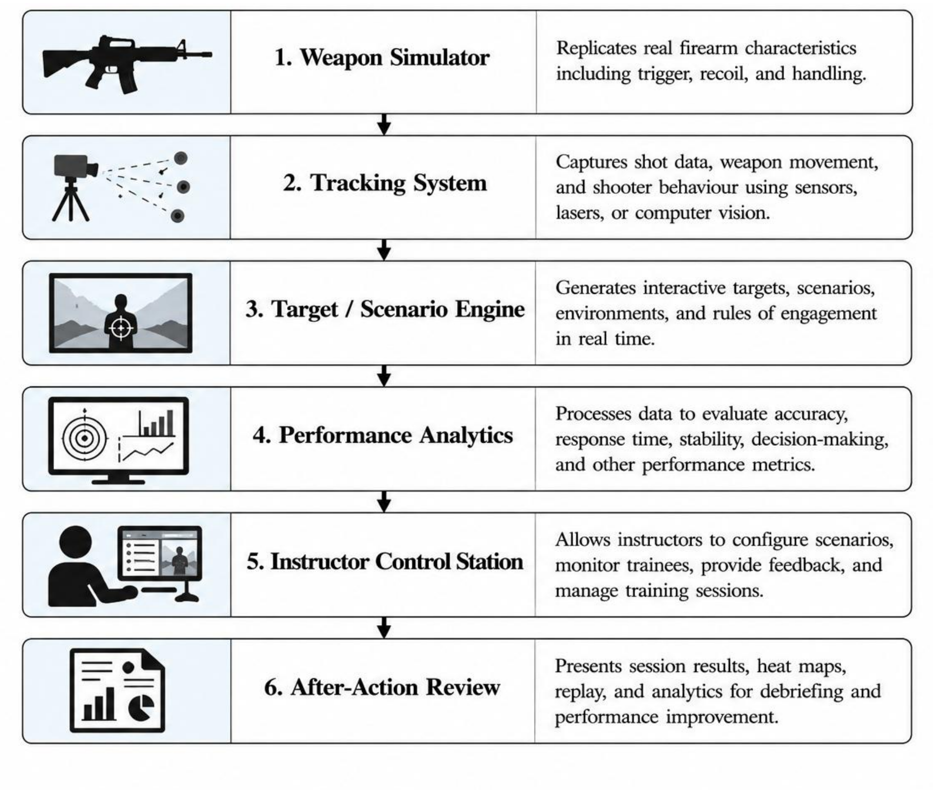

Fig. 15: Generic Architecture of Commercial Marksmanship Simulators

To facilitate objective comparison of different systems, a Composite System Performance Index (CSPI) may be defined as:

$$CSPI = w_1R + w_2A + w_3I + w_4T + w_5C \qquad (34)$$

where: R= realism score, A= tracking and scoring accuracy, I= immersion score, T= training effectiveness score and C= cost-effectiveness score. The weighting coefficients satisfy:

$$\sum_{i=1}^{5} w_i = 1 \qquad (35)$$

A comparison of representative commercial systems is presented in Table 15.

Table 15: Comparative Assessment of Representative Commercial Systems

System	Primary Technology	Recoil Simulation	AI Features	Immersion Level	Military Usage
VirTra V-300	Projection-based	Optional	Limited	High	High
Laser Shot	Laser-based	Optional	Limited	Moderate	Moderate
InVeris FATS®	Integrated laser/video	Yes	Moderate	High	Very High
Saab GAMER	Tactical simulation	Yes	Limited	High	Very High
Cubic Training Systems	Integrated simulation	Yes	Moderate	High	High

The principal strengths and limitations of the major technology categories are summarised in Table 16.

Table 16: Strengths and Limitations of Commercial Systems

Technology	Strengths	Limitations
Laser-Based	Low cost, easy deployment, safe operation	Limited immersion and scenario realism
Projection-Based	High visual realism and scenario flexibility	Greater infrastructure requirements
Computer Vision	Detailed performance analytics	Higher computational demands
VR/AR/MR	High immersion and cognitive engagement	Potential simulator sickness and hardware cost
AI-Assisted	Adaptive coaching and predictive assessment	Requires large datasets and model validation
Hybrid Integrated	Comprehensive training capability	High acquisition and maintenance costs

Overall, the industry is moving towards hybrid intelligent training ecosystems that combine computer vision, immersive simulation, biometric sensing, AI-driven analytics, cloud-based data management, and digital-twin technologies. Future systems are expected to incorporate explainable artificial intelligence (XAI), federated learning, collaborative virtual environments, and distributed simulation architectures capable of supporting large-scale, multi-domain military training operations. These developments are likely to enhance training realism, improve skill acquisition and retention, and provide increasingly personalised and data-driven training experiences.

10. Military Adoption and Operational Validation

The increasing adoption of indoor marksmanship simulation technologies by military and law-enforcement organisations worldwide provides strong evidence of their operational effectiveness and training value. As modern armed forces seek to enhance combat readiness while reducing training costs, ammunition consumption, and safety risks, simulation-based marksmanship systems have become an integral component of contemporary military training architectures. These systems enable frequent, repeatable, and objective training within controlled environments while complementing conventional live-fire exercises [22], [30], [117]–[120]. Representative examples of military adoption and operational applications are summarised in Table 17.

Among the most prominent users, the U.S. Army employs the Engagement Skills Trainer (EST 2000) and the Integrated Visual Augmentation System (IVAS) to support individual weapon proficiency, collective tactical training, mission rehearsal, and soldier readiness programmes [126], [127]. Similarly, the U.S. Marine Corps utilises the Indoor Simulated Marksmanship Trainer (ISMT) to develop combat marksmanship skills and reinforce shooting fundamentals before live-fire qualification [128]. In Europe, the British Army employs the Dismounted Close Combat Trainer (DCCT) and related synthetic training systems to support urban warfare, close-quarter battle (CQB), and tactical decision-making exercises [129]. Several NATO member states have likewise integrated simulator-based marksmanship training into combat-readiness programmes to improve training efficiency while reducing operating costs and environmental impacts [22], [30], [119].

In the Asia-Pacific region, the Singapore Armed Forces (SAF) have incorporated advanced indoor simulation systems into their integrated soldier-training framework, particularly for urban operations, force-on-force exercises, and tactical decision-making training [130]. Comparable initiatives have been implemented within the armed forces of Australia, South Korea, and Israel, where simulation technologies are increasingly used to enhance mission preparation, operational readiness, and training-resource optimisation [54], [75], [120]. The diverse applications and benefits realised by these organisations further demonstrate the growing role of simulation technologies in modern military training. Table 17 presents representative examples of military adoption of marksmanship simulation systems and their operational applications.

Table 17: Examples of Military Adoption of Marksmanship Simulation Systems

Organisation	System	Primary Application	Operational Benefit
U.S. Army	EST 2000	Rifle and squad weapons training	Reduced ammunition expenditure; increased training frequency
U.S. Army	IVAS	Tactical mission rehearsal and soldier training	Enhanced situational awareness and decision-making
U.S. Marine Corps	ISMT	Combat marksmanship training	Improved shooting proficiency before live-fire qualification
British Armed Forces	DCCT	Close-quarter battle and urban operations	Enhanced tactical decision-making and readiness
Singapore Armed Forces	Indoor simulation systems	Urban warfare and force-on-force training	Improved operational readiness
Australian Defence Force	Weapons simulation systems	Individual and collective training	Increased training efficiency
Israeli Defence Forces	Tactical marksmanship simulators	Urban combat preparation	Enhanced mission rehearsal capability
Nigerian Defence Academy	KOLSKOT Marksmanship Training System	Officer-cadet marksmanship instruction and performance assessment	Improved shooting proficiency, safety, and training continuity
NATO Training Centres	Synthetic training systems	Collective combat training	Reduced cost and improved training scalability

In Africa, the Nigerian Defence Academy (NDA), Kaduna, has also embraced simulation-based marksmanship training through the establishment of a Small Arms Simulation Shooting Range commissioned in 2022. The facility enables repetitive shooting practice, weapon-handling drills, and objective performance assessment within a safe and controlled environment. The Academy additionally employs the KOLSKOT electronic marksmanship training system for precision shooting instruction and performance evaluation. These capabilities support year-round training, reduce dependence on live-range availability, improve safety, and provide data-driven assessment of cadet performance while conserving training resources. The NDA experience demonstrates the increasing recognition of synthetic training environments as force multipliers for military education, officer development, and readiness generation within emerging defence institutions [131].

Evidence from operational studies and military training programmes indicates that simulator-based marksmanship training can improve weapon handling, aiming stability, reaction time, situational awareness, and overall training throughput while significantly reducing ammunition expenditure and range utilisation requirements [22], [117], [118], [120]. Although simulation systems cannot fully replicate the psychological stress, environmental uncertainty, and physiological demands of live combat engagements, numerous military organisations have demonstrated that combining simulator-based instruction with periodic live-fire validation produces superior training outcomes compared with reliance on live-fire training alone [9], [22], [30], [119].Overall, the military adoption examples presented in Table 17 illustrate that indoor marksmanship simulators have evolved from supplementary instructional aids into essential components of modern military training ecosystems. Their ability to enhance training effectiveness, improve safety, optimise resource utilisation, and support continuous readiness generation underscores their growing importance in preparing personnel for contemporary operational environments [22], [30], [117]–[120].

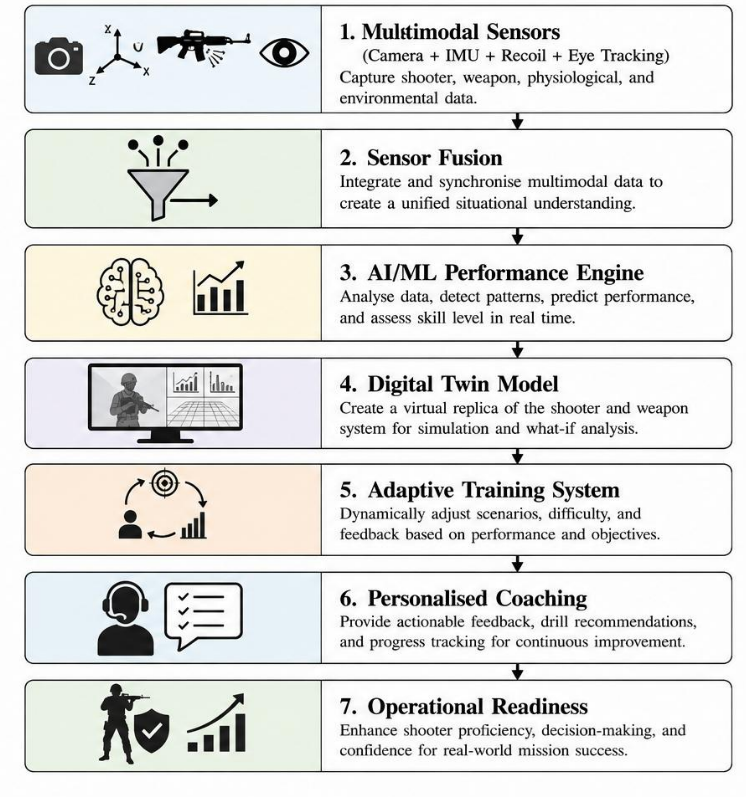

Fig. 16: Future Intelligent Marksmanship Training Ecosystem.

11. Research Gaps and Future Directions

Despite significant advances in indoor marksmanship simulation technologies, several technical, operational, and human-centred challenges remain unresolved. Current systems have achieved considerable success in shot localisation, recoil simulation, immersive visualisation, and performance assessment; however, important limitations continue to affect training realism, scalability, adaptability, and transferability to operational environments [1]–[120]. A summary of the principal research gaps identified from the literature is presented in Table 18.

Table 18: Major Research Gaps in Indoor Marksmanship Simulation

Research Area	Current Limitation	Future Research Direction
Recoil Simulation	Limited weapon-specific realism	Adaptive recoil modelling and digital twins
Computer Vision	Sensitivity to lighting and occlusion	Robust multimodal sensor fusion
AI Assessment	Limited explainability	Explainable AI (XAI) systems
VR/AR/MR Training	Simulator sickness and latency	Low-latency immersive architectures
Human Factors	Incomplete cognitive assessment	Cognitive-state monitoring
Commercial Systems	High acquisition cost	Low-cost modular architectures
Training Evaluation	Limited long-term validation	Longitudinal performance studies

As illustrated in Fig. 16, future indoor marksmanship simulators are expected to evolve toward fully integrated intelligent training ecosystems that combine multimodal sensing, AI immersive environments, physiological monitoring, and digital-twin technologies.

One major research gap concerns the limited ability of existing simulators to accurately reproduce weapon-specific recoil signatures. Current pneumatic and electromechanical systems typically generate generic recoil profiles that fail to fully capture bolt-carrier dynamics, vibration spectra, muzzle climb characteristics, and shooter–weapon interaction effects. Future studies should investigate physics-based digital twins and adaptive recoil-generation algorithms capable of replicating individual weapon systems with higher fidelity [53]–[61].

Another important challenge relates to the robustness of computer vision systems. Although recent advances in deep learning have significantly improved target detection and pose estimation performance, vision-based systems remain susceptible to lighting variations, motion blur, occlusions, and environmental clutter. Future systems should integrate computer vision, inertial sensing, laser tracking, and physiological monitoring through multimodal sensor-fusion frameworks [62]–[80]. AI represents one of the most promising areas for future development. Current AI-enabled simulators primarily focus on performance assessment and adaptive coaching. However, emerging concepts such as explainable AI (XAI), reinforcement learning, federated learning, and digital twins could enable more transparent, scalable, and personalised training systems [91]–[104].

The growing availability of wearable sensors presents opportunities for physiological-state monitoring. Future simulators may incorporate electroencephalography (EEG), electromyography (EMG), heart-rate variability (HRV), galvanic skin response (GSR), and eye-tracking systems to assess stress, fatigue, attention, and cognitive workload during training exercises [111]–[120]. Another critical research gap concerns the limited availability of longitudinal validation studies. Most published studies evaluate simulator effectiveness over relatively short experimental periods. Comprehensive long-term investigations involving military personnel, law-enforcement officers, and civilian shooters are required to establish the relationship between simulator performance and operational effectiveness.

The integration of digital twins represents another emerging research direction. Digital-twin technologies could enable continuous modelling of individual shooter behaviour, allowing training systems to predict performance trends, identify weaknesses, and generate personalised training programmes. Such capabilities are expected to significantly improve training efficiency and readiness assessment. Future indoor marksmanship simulators are therefore expected to transition from standalone training devices to intelligent decision-support systems capable of continuously monitoring, predicting, and enhancing shooter performance throughout the training lifecycle.

12. Discussion

The review demonstrates that indoor marksmanship simulation technologies have evolved significantly from basic laser-based shot-detection systems into sophisticated training ecosystems incorporating computer vision, artificial intelligence (AI), immersive virtual environments, physiological monitoring, and digital-twin technologies. This evolution reflects the growing demand for training solutions capable of enhancing combat readiness while reducing ammunition expenditure, safety risks, environmental constraints, and training costs. As military organisations increasingly seek efficient and scalable methods for maintaining operational proficiency, simulation-based marksmanship training has emerged as an indispensable component of modern military training architectures.

A key finding of this review is that no single technology satisfies all military training requirements. Rather, each technology possesses distinct strengths and limitations depending on the intended training objectives. Laser-based systems remain highly attractive for recruit training, weapon familiarisation, and routine marksmanship practice because they are relatively inexpensive, easy to deploy, highly scalable, and capable of supporting large numbers of trainees simultaneously. These characteristics largely explain their widespread adoption within military academies, training schools, and law-enforcement organisations worldwide. However, their inability to accurately reproduce recoil effects, environmental influences, target behaviour, and battlefield stress limits their effectiveness for advanced combat training and tactical decision-making exercises.

Computer vision and optical tracking systems have emerged as powerful tools for objective performance assessment. Unlike traditional instructor-based evaluation methods, these technologies provide quantitative measurements of aiming behaviour, trigger control, muzzle movement, weapon stability, posture, target engagement sequence, and reaction time. Their increasing success can be attributed to advances in imaging sensors, high-speed cameras, machine-learning algorithms, and computational processing capabilities. Nevertheless, their effectiveness remains dependent on sensor calibration, image quality, environmental conditions, and processing infrastructure. Consequently, while these systems offer substantial analytical advantages, their deployment in austere or resource-constrained environments may be limited by technical and logistical requirements.

The review further indicates that recoil simulation constitutes a critical factor influencing training realism and skill transfer. Realistic recoil reproduction improves weapon handling, target reacquisition, follow-through behaviour, and shooter confidence. Numerous studies have shown that training transfer improves significantly when simulator recoil characteristics closely resemble those of operational weapons. However, increasing recoil fidelity typically results in greater acquisition costs, higher maintenance requirements, and increased system complexity. This trade-off helps explain why many military organisations continue to adopt blended training approaches that combine low-cost laser systems for routine practice with higher-fidelity simulators for advanced marksmanship instruction.

Immersive technologies, including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), offer substantial advantages for tactical training, mission rehearsal, situational awareness development, and collective training activities. Their ability to recreate complex operational scenarios such as urban warfare, convoy protection, room-clearing operations, hostage rescue, and close-quarter battle (CQB) provides training opportunities that would otherwise be difficult, costly, or unsafe to conduct repeatedly using live exercises. Despite these advantages, widespread adoption remains constrained by factors such as simulator sickness, motion-to-photon latency, infrastructure requirements, hardware costs, and long-term sustainment considerations. These limitations help explain why immersive technologies are currently employed primarily as complementary training tools rather than complete substitutes for live-fire exercises.

Artificial intelligence represents one of the most transformative developments in contemporary marksmanship training. AI-enabled systems can automate performance assessment, identify behavioural patterns, predict trainee progression, generate personalised coaching recommendations, and optimise training pathways. The effectiveness of these systems is driven by the availability of large training datasets, advances in deep learning, and increasing computational power. However, military adoption remains influenced by concerns relating to explainability, transparency, cybersecurity, data quality, and algorithmic bias. In defence applications, AI-generated recommendations must remain interpretable, verifiable, and trusted by instructors and commanders. Consequently, explainable AI, human-centred AI, and trustworthy AI frameworks are likely to become increasingly important components of future military training systems.

From a cost-benefit perspective, substantial differences exist among the technologies reviewed. Laser-based systems offer the lowest acquisition and operating costs while providing excellent scalability and ease of deployment. Computer vision systems provide improved performance assessment capabilities at moderate cost, whereas immersive VR, AR, and MR systems require significantly greater investment in hardware, software, infrastructure, and maintenance. Hybrid integrated systems combining laser tracking, computer vision, recoil simulation, immersive visualisation, and AI typically provide the highest training effectiveness but also incur the greatest lifecycle costs. Consequently, technology selection should be driven by operational requirements, training objectives, available resources, and sustainment considerations rather than technological sophistication alone.

Table 19: Technology Readiness and Military Suitability Assessment

Technology	TRL	Military Suitability	Cost	Adoption Potential
Laser-Based	9	Very High	Low	Very High
Optical Tracking	9	High	Medium	High
Computer Vision	8–9	High	Medium–High	High
Recoil Simulation	8–9	High	Medium–High	High
VR	8	High	High	Medium–High
AR	7–8	High	High	High
MR	7–8	Very High	High	High
AI-Assisted	7–8	Very High	High	Very High
Digital Twin	5–7	Emerging	Very High	High
Hybrid Systems	8	Very High	Very High	Very High

Technology readiness also varies considerably across the technologies reviewed. As shown in Table 19, laser-based simulators, optical tracking systems, and recoil simulation technologies have achieved high levels of maturity, with Technology Readiness Levels (TRLs) approaching full operational deployment. These technologies are already widely employed by military and law-enforcement organisations because of their proven reliability, established training methodologies, and relatively low implementation risk. Computer vision-based systems are approaching similar maturity levels as advances in sensing, AI, and computational hardware continue to improve performance and robustness. In contrast, digital twins, adaptive AI coaching systems, and metaverse-based training environments remain at comparatively lower readiness levels despite their significant future potential. The assessment presented in Table 19 further demonstrates that technologies with the highest military suitability are not necessarily those with the highest technological sophistication. Instead, successful adoption depends on achieving an appropriate balance among operational effectiveness, affordability, scalability, maintainability, interoperability, and technology maturity.

The technology readiness assessment presented in Table 19 suggests that future research and development efforts should prioritise validation, interoperability, cybersecurity, human-system integration, and operational testing of emerging capabilities before large-scale military adoption. Particular attention should be directed toward digital twins, explainable AI, adaptive coaching systems, and integrated metaverse-based training environments, which offer substantial operational benefits but require further validation under realistic military training conditions. Future studies should also investigate long-term training transfer, human performance under operational stress, and the effectiveness of AI-driven coaching in comparison with conventional instructor-led training approaches.

The military adoption examples presented in Table 17 provide compelling evidence that simulation technologies have transitioned from supplementary instructional aids to essential components of modern military training ecosystems. Organisations such as the U.S. Army, U.S. Marine Corps, British Army, Singapore Armed Forces, and the Nigerian Defence Academy have demonstrated the practical benefits of simulation-based marksmanship training in improving readiness, increasing training throughput, reducing ammunition consumption, and enhancing safety. These operational experiences indicate that the greatest benefits are achieved when simulator-based training complements rather than replaces live-fire training programmes.

Overall, the evidence reviewed suggests that future marksmanship training systems will increasingly adopt hybrid intelligent architectures that combine laser tracking, computer vision, recoil simulation, immersive environments, physiological monitoring, digital twins, and explainable artificial intelligence within unified training ecosystems. Such integrated systems are expected to deliver higher levels of realism, adaptability, personalisation, and training effectiveness while supporting continuous readiness generation across a broad spectrum of military operational environments. As defence organisations continue to pursue cost-effective methods for enhancing combat preparedness, simulation-based marksmanship technologies are likely to play an increasingly central role in the future of military training and operational readiness.

12. Conclusion

Indoor marksmanship simulation technologies have become indispensable components of contemporary military and law-enforcement training systems, offering safe, scalable, cost-effective, and repeatable alternatives to conventional live-fire training. This review has comprehensively examined the evolution, principles, capabilities, and applications of major simulation technologies, including laser-based systems, optical tracking technologies, recoil simulation systems, computer vision and high-speed imaging platforms, immersive VR/AR/MR environments, and AI-enabled training systems. The review further evaluated human factors, training effectiveness, commercial solutions, military adoption trends, and emerging intelligent training ecosystems.

The analysis reveals that no single technology independently satisfies all military training requirements. Laser-based systems provide affordability and scalability for basic marksmanship instruction, whereas computer vision and optical tracking systems enable objective performance assessment and detailed behavioural analysis. Recoil simulation technologies improve realism and training transfer, while immersive VR, AR, and MR systems enhance tactical decision-making, situational awareness, and mission rehearsal. AI-enabled systems further transform marksmanship training through adaptive coaching, predictive analytics, automated assessment, and personalised learning pathways. Collectively, these technologies contribute to improved training efficiency, reduced resource consumption, enhanced safety, and increased operational readiness.

A key finding of this review is that the most effective military training solutions are likely to emerge from the integration of complementary technologies rather than reliance on any single approach. The military adoption examples reviewed, including those from the U.S. Army, U.S. Marine Corps, British Army, Singapore Armed Forces, NATO training establishments, and the Nigerian Defence Academy, demonstrate that simulation-based marksmanship training has evolved from a supplementary instructional aid into an essential component of modern military training architectures. These systems have proven particularly valuable for increasing training frequency, reducing ammunition expenditure, improving instructor effectiveness, and supporting continuous readiness generation.

Despite substantial progress, important challenges remain. These include improving training-transfer validation, increasing realism, mitigating simulator sickness, ensuring AI transparency and trustworthiness, strengthening cybersecurity, enhancing interoperability, and reducing lifecycle costs. Emerging technologies such as digital twins, multimodal sensor fusion, physiological monitoring, explainable artificial intelligence, federated learning, and metaverse-enabled training environments are expected to address many of these limitations and further enhance training effectiveness. Overall, the evidence reviewed indicates that future indoor marksmanship training systems will increasingly evolve toward intelligent, adaptive, and fully integrated training ecosystems capable of simultaneously developing technical shooting proficiency, tactical competence, cognitive performance, and decision-making skills. For military organisations seeking to improve combat effectiveness while optimising training resources, simulation-based marksmanship technologies represent a critical force multiplier and will remain central to the development of mission-ready personnel in future operational environments.

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