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A Critical Analysis of Existing Technologies in Squash Training: Towards an Automated Training Court

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ABSTRACT

The integration of technology into sports training has transformed performance analysis across many disciplines, yet its adoption in squash has been comparatively limited. Existing tools, ranging from image and video processing to sensor-based systems and emerging artificial intelligence applications, typically measure discrete aspects such as player positioning, ball trajectory, or racket motion but rarely operate in an integrated manner. This review synthesizes evidence to identify persistent technological gaps in squash, focusing on challenges of real-time accuracy, environmental constraints of the court, inconsistent standards across systems, and the scarcity of sport-specific datasets. Usability and cost barriers further restrict access, particularly for junior, para, and community-level athletes. Addressing these limitations is essential if technological solutions are to progress from isolated analytics toward comprehensive, accessible tools capable of transforming training practices in the sport.

Keywords:- squash training

I. INTRODUCTION

Technology has become a defining feature of modern sports training, offering athletes new ways to monitor, analyze, and refine performance. In disciplines such as tennis, football, and athletics, innovations in motion tracking, wearable sensors, and artificial intelligence have shifted coaching from a predominantly observational practice to a data-driven endeavor. Real-time statistics, biomechanical analysis, and predictive modeling are now widely integrated into elite environments and are gradually filtering down to community and youth levels. These developments have altered not only how performance is measured but also how tactical and strategic decisions are made during practice and competition.

Despite these advances in other sports, squash remains a relatively underexplored case in the field of technology-assisted training. As a fast-paced, indoor racquet sport with unique spatial and tactical demands, squash presents specific barriers for performance monitoring. The confined court, frequent player overlap, and rapid exchanges complicate traditional tracking methods. Unlike tennis or badminton, where player movements and ball trajectories can be captured with fewer obstructions, squash requires more complex systems to deliver reliable data. Consequently, the integration of advanced technological tools in squash has lagged behind, leaving a fragmented landscape of partially effective solutions.

Existing tools for squash tend to address isolated aspects of performance. Video-based systems provide tactical insights, wearable sensors track swing dynamics and workload, and commercial platforms are experimenting with artificial intelligence for shot classification and rally reconstruction. However, these technologies rarely interact, resulting in siloed outputs that are difficult for coaches and players to interpret holistically. As a result, even professional squash athletes still rely heavily on traditional observation and subjective feedback. While valuable, such methods lack the objectivity and precision that integrated technology could offer.

The slow pace of innovation in squash training arises from technical, practical, and economic challenges. The court geometry makes unobstructed video capture difficult, especially when players obscure one another or the ball. The rapid nature of rallies demands high-frame-rate cameras and advanced algorithms capable of real-time analysis. Wearable devices face barriers of accuracy, comfort, and standardization, while the sport's smaller global market compared to tennis or football reduces incentives for large-scale commercial investment. As a result, most innovations emerge from research prototypes or niche startups rather than validated, widely adopted systems.

This paper addresses these challenges by critically examining the current technological landscape in squash training. Specifically, the review evaluates available tools in four domains—image and video processing, sensor-based systems, artificial intelligence and machine learning, and virtual or augmented reality. Within each domain, the discussion highlights both contributions and limitations.

The scope of this study is conceptual rather than experimental. No new technologies are tested directly; instead, findings from existing literature are synthesized to identify recurring challenges and persistent barriers. By grounding the analysis in squash-specific contexts, the paper avoids overgeneralizations from other racquet sports and provides a more accurate account of the sport's unique demands.

The significance of this investigation lies in its potential to guide future innovation. By clarifying why squash-specific technologies have lagged and identifying the gaps they face, possible pathways toward more integrated and effective systems can be proposed. This paper therefore contributes to both academic discussions on sports technology and the practical needs of athletes, coaches, and developers seeking to modernize training practices in squash.

In summary, squash's fast pace, constrained environment, and tactical complexity make it both a promising candidate for technological support and a difficult sport in which to implement effective systems. This paper asks: Why have squash-specific technologies lagged, and how can an integrated framework overcome these limitations? To answer this, the following sections analyze existing technologies, examine their shortcomings, and propose directions for future innovation.

II. IMAGE AND VIDEO PROCESSING SYSTEMS (BALL TRACKING, PLAYER TRACKING, MOTION ANALYSIS)

A. Data Acquisition and Instrumentation

Image pipelines begin with video capture. Squash research typically uses two types of sources: (a) broadcast or competition video (single rear camera, common in PSA archives) and (b) purpose-built multi-camera rigs (ceiling- or wall-mounted) for laboratory or club analyses. Baclig et al. (2020) demonstrated a pipeline using broadcast footage at 25 fps and 720 × 576 resolution to extract kinematic metrics from elite matches. Other systems—both research and commercial—deploy high-frame-rate cameras or multi-camera arrays to improve metric accuracy and enable depth recovery (Baclig et al., 2020; Brumann et al., 2021).

Key acquisition variables documented in squash studies include:

- **Frame rate and exposure** — Ball and impact detection benefit from higher frame rates. Most squash analyses use 25–60 fps broadcast video (Baclig et al., 2020), with purpose-built cameras employed when finer temporal resolution is needed.
- **Camera geometry** — Single fixed rear/center cameras (common in broadcast) versus multi-angle arrays (ceiling or side-mounted), which enable triangulation and inverse-perspective mapping (Baclig et al., 2020; Vučković et al., 2014).

B. Preprocessing and Court Calibration

Preprocessing converts pixel coordinates into standardized court coordinates via homography or inverse-perspective mapping. Typical steps include:

1. **Frame selection** — Isolating in-play frames (Baclig et al., 2020).
2. **Court calibration** — Detecting or manually setting reference points (corners, lines) to compute a planar homography mapping pixels to a 2D court plane. Vučković et al. (2014) used annotated reference points from behind-court views to assign ball bounces reliably to their 15-zone partitioning.
3. **Image normalization** — Color balancing, denoising, and occasional background subtraction (for small-object detection) before detector input.

C. Player Detection, Pose Estimation, and Tracking

Two main approaches appear in the literature:

a) **Bounding-box detectors with trackers** (tracking-by-detection): Object detectors such as YOLO variants, Faster R-CNN, or SSD generate person bounding boxes per frame, which are then linked by trackers (e.g., SORT, DeepSORT) using motion prediction and appearance descriptors. This architecture is common in multi-person sport tracking and underlies many squash proof-of-concepts.

b) **Human-pose estimation (HPE) pipelines**: Modern squash studies increasingly adopt HPE methods, as pose keypoints yield richer kinematic features (e.g., limb angles, foot positions). OpenPose (Cao et al., 2017), HRNet (Sun et al., 2019), and related networks are widely referenced. Brumann et al. (2021) systematically benchmarked over 250 HPE models, selecting pre-trained networks suitable for squash foot detection and heatmap generation.

A typical squash HPE–tracking pipeline proceeds as follows:

1. **HPE inference** per frame → body/foot/keypoint heatmaps.
2. **Keypoint grouping** → assemble skeletons using part-affinity fields or affinity scoring.
3. **Identity association** → maintain skeleton continuity across frames using Kalman filtering, appearance embeddings, or heuristic matching (SORT/DeepSORT adaptations).
4. **Court mapping** → apply homography to convert keypoints into court-plane coordinates, enabling metrics such as distance covered, time on the T, and velocity (Baclig et al., 2020).

Outputs from these pipelines include per-frame player positions, velocity/acceleration measures, central-T heatmaps, left/right foot step counts, step cadence, and lunge biomechanics when sufficient keypoints are detected (Brumann et al., 2021; Baclig et al., 2020).

D. Ball Detection and Trajectory Reconstruction

Ball tracking is treated separately due to the ball's small size, high speed, and frequent occlusion. Reported approaches include:

1. **Direct detection** — Training detectors for small-object recognition. Frame differencing and motion-based proposals are effective when resolution permits. With multiple views, triangulation can improve accuracy, but broadcast footage often limits visibility (Baclig et al., 2020).
2. **Predictive interpolation/physics priors** — Algorithms fit ballistic motion models or spline curves constrained by ball dynamics to interpolate gaps in detection. Multi-view setups allow full 3D trajectories.
3. **Audio fusion** — Microphone arrays (e.g., 96 kHz sampling) detect impacts and localize them using time-of-arrival differences. Audio signatures also enable shot-type classification and impact-energy estimation (Hajdú-Szücs et al., 2018).

E. Event Segmentation and Labelling

After detection, events are grouped into rallies and labelled (e.g., shot type classification using video windows ± audio cues). Vučković et al.'s (2014) 15-zone taxonomy is frequently applied for tactical categorization.

F. Evaluation and Reported Outputs

Evaluation metrics vary by task: mean absolute percent error for kinematic estimates (Baclig et al., 2020), precision/recall or average precision for detection, and motion-density heatmap comparisons for tracking outputs (Brumann et al., 2021).

III. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS (PATTERN RECOGNITION, PREDICTIVE ANALYTICS)

The squash analytics stack typically follows a layered architecture: **low-level feature extraction** (from video, IMU, or audio) → **mid-level event and shot classification** → **high-level sequence modeling and predictive analysis**.

G. Feature Extraction

Inputs to machine learning models derive from multiple modalities:

- **Visual features** — Keypoint coordinates, bounding boxes, optical flow, and localized image patches around racket, ball, or impact regions. HPE networks such as OpenPose (Cao et al., 2017) and HRNet (Sun et al., 2019) supply skeleton features for tactical and biomechanical modeling.
- **Sensor features** — IMU acceleration and gyroscope signals, including time-domain features (peak magnitude, RMS), frequency-domain features (spectral energy near impact), and derived biomechanics metrics (swing angular velocity). Racket-mounted devices typically output per-shot summaries (e.g., impact timestamp, swing duration).
- **Audio features** — Event onset times, spectrogram slices, and time-difference-of-arrival (TDOA) localization outputs. Hajdú-Szücs et al. (2018)

demonstrated their use in both localization and shot classification.

H. Shot Classification and Pattern Recognition

Two main categories of models are applied:

- **Frame/snippet classifiers** — Convolutional neural networks (CNNs) or CNNs with temporal pooling are used to classify shot types (drive, drop, boast, volley). For motion dependencies, 3D CNNs (e.g., C3D) or two-stream networks (RGB + optical flow) capture temporal dynamics. Baclig et al. (2020) employed per-shot visual features combined with pose cues for classification.
- **Sequence models** — Recurrent neural networks (e.g., LSTMs) model shot-to-shot dependencies within rallies, learning tactical transitions such as probability of a defensive lob following backcourt pressure. These models are trained on annotated rally sequences and are applied for rally reconstruction, motif discovery, and tactical analysis (Baclig et al., 2020).

I. Predictive Analytics and Tactical Inference

ML-based prediction has been applied to tactical forecasting and player profiling:

- **Rally outcome prediction** — Supervised models (logistic regression, random forests, neural networks) map state vectors (player positions, fatigue proxies, last shot type) to probabilities of rally outcomes or next-shot types. Commercial platforms highlight such outputs as "key moment" analyses.
- **Opponent profiling and style clustering** — Unsupervised methods (k-means, hierarchical clustering, HMMs) identify archetypes such as short-game aggressors versus attrition players. Vučković et al.'s (2014) 15-zone mapping often provides the feature basis for these analyses.

Model Training and Data Considerations

Model development in squash research is shaped by limited dataset availability:

- **Annotation pipelines** — Brumann et al. (2021) developed a squash-specific dataset with frame-level foot annotations, while Baclig et al. (2020) used manually tracked frames as validation ground truth. Manual annotation remains critical due to the absence of large public corpora.
- **Transfer and pre-training** — Many studies adapt models pre-trained on general datasets (e.g., COCO, MPII) for pose and detection tasks, with OpenPose and HRNet forming the most common backbones (Cao et al., 2017; Sun et al., 2019).
- **Evaluation practices** — Performance is typically reported using detection average precision (AP), tracking measures such as MOTA/MOTP, rally classification accuracy, and kinematic error versus manual labels. Baclig et al. (2020) reported mean absolute percent errors of ~3–4% for distance and speed estimates.

IV. SENSOR TECHNOLOGIES (WEARABLES, RACKET SENSORS, COURT SENSORS)

J. Racket-Mounted Sensors

The most common form factor is a small IMU module mounted at the butt of the racket, typically sampling at several hundred Hz. For example, Racketware reports sampling rates up to ~500 Hz, with data streamed to a mobile app (Racketware, 2021). These systems measure acceleration and angular velocity, either computing features on-device or post-processing them on paired devices. Derived metrics include peak acceleration, swing duration, racket head speed, impact angle, and heuristic shot labels.

Typical signal processing steps are:

1. **Onset detection** — Identifying impact via short, high-magnitude acceleration spikes with adaptive thresholds.
2. **Window extraction** — Capturing fixed-length signal windows around impact (e.g., ±50 ms).
3. **Feature extraction** — Deriving time-domain (peak, impulse, RMS), frequency-domain (spectral centroid), and waveform-shape descriptors (e.g., zero-crossing).
4. **Shot classification** — Applying shallow classifiers (SVMs, decision trees) or compact neural networks for per-shot labelling.

K. Wearable IMUs and Physiological Sensors

IMUs positioned on the wrist, ankle, or torso produce continuous acceleration and angular velocity streams, which are used to quantify workload (e.g., step detection, lunge counts, peak accelerations). When fused with vision-based tracking via homography, IMU data can be mapped to court locations. Prototypes with synchronized IMUs have been employed to study explosive movements and lunge biomechanics.

Processing typically involves integration to estimate velocity (with drift correction), activity recognition through temporal models, and workload indices (e.g., PlayerLoad-style metrics).

L. Smart-Court Sensors and Environmental Instrumentation

Instrumented court systems integrate multiple sensing modalities: ceiling-mounted cameras, floor-embedded pressure sensors, microphone arrays, and projection systems (PSA & interactiveSQUASH, 2018). These environments generate court-referenced data directly—such as player footprints and ball bounce locations—without requiring external camera homography per match.

Smart courts typically fuse camera-based detections, embedded sensor data, and racket IMU outputs using synchronized timestamps, enabling richer event records (e.g., impact localization, shot type labelling, workload analysis). For example, Hajdú-Szücs et al. (2018) demonstrated high-accuracy ball impact localization using multi-channel audio sampled at 96 kHz.

V. OTHER RELEVANT TOOLS — COMPARISONS WITH TENNIS & BADMINTON SYSTEMS (TECHNOLOGY PRIMITIVES AND ADOPTED PRACTICES)

M. Tennis and Hawk-Eye (Multi-Camera Triangulation)

Hawk-Eye represents the gold standard in racket sport tracking, employing multiple high-speed cameras (hundreds of fps) placed around the court to achieve millimeter-level trajectory reconstruction (Hawk-Eye Innovations, n.d.). The system applies subpixel ball detection per view, multi-camera triangulation, and model-based smoothing (e.g., Kalman filters) to generate precise 3D trajectories and line calls. Outputs include replay visualizations, shot speeds, and landing point accuracy.

While conceptually transferable to squash, this approach faces domain-specific challenges: the enclosed court architecture and the squash ball's higher incidence of wall interactions require adaptations in camera placement, calibration, and trajectory modeling.

N. Badminton Shuttle Tracking

Badminton tracking systems must account for extreme shuttle velocities and rapid deceleration. Research solutions deploy high-frame-rate, multi-view camera setups combined with motion-blur compensation and aerodynamics-aware motion models. The shuttlecock's unique flight dynamics necessitate specialized detectors and trajectory algorithms.

These design adaptations illustrate how domain-specific physics shape engineering choices—principles that can be applied to squash, where the ball's frequent occlusions and wall bounces similarly demand tailored tracking solutions.

O. Adoption in Squash Systems

Squash research and commercial platforms have adopted primitives from these domains, combining:

- HPE models (OpenPose, HRNet) for player pose detection,
- Detection–tracking pipelines (YOLO + SORT/DeepSORT) for bounding-box tracking,
- Audio or IMU fusion where visual data is insufficient (Hajdú-Szücs et al., 2018; Baclig et al., 2020; Brumann et al., 2021).

Commercial platforms such as SmartSquash, Core Analytics, Rally Vision, and interactiveSQUASH provide end-user workflows built on these primitives, typically structured as: **video upload → automated processing (pose/detection → tracking → event segmentation) → analytics dashboard**. These systems demonstrate the practical integration of research pipelines into coach- and player-facing tools.

Domain	Technology/Method	Key Features	Applications in Squash	References
Video Acquisition	Broadcast video (25–60 fps)	Single fixed rear/center camera	Kinematic analysis from PSA footage	Baclig et al. (2020)
	Multi-camera rigs (high fps)	Ceiling/side placement, depth recovery	Lab-based trajectory and motion studies	Brumann et al. (2021)
Preprocessing	Court calibration (homography)	Reference points, 2D mapping	Bounce location to tactical zones	Vučković et al. (2014)
	Image normalization	Color balance, denoising, background subtraction	Improved detection accuracy	Baclig et al. (2020)
Player Tracking	Bounding-box + tracker (YOLO, Faster R-CNN + SORT/DeepSORT)	Per-frame bounding boxes with identity continuity	Multi-player tracking	Baclig et al. (2020)
	Human Pose Estimation (OpenPose, HRNet)	Keypoints, skeletons, heatmaps	Biomechanics, footwork, lunge detection	Brumann et al. (2021)
Ball Tracking	Visual detection	Small-object detectors, motion differencing	Ball trajectory estimation	Baclig et al. (2020)
	Physics-informed interpolation	Ballistic models, spline fitting	Fill detection gaps	Baclig et al. (2020)
	Audio fusion	96 kHz mic arrays, TDOA localization	Impact detection, shot classification	Hajdú-Szücs et al. (2018)
AI/ML Applications	CNNs / 3D CNNs / Two-stream networks	Frame/snippet shot classification	Drive, drop, boast, volley recognition	Baclig et al. (2020)
	RNNs / LSTMs	Rally sequence modeling	Tactical transitions, motif discovery	Baclig et al. (2020)
	Supervised classifiers (logistic regression, RF, NN)	State-based predictions	Rally outcome forecasting	Brumann et al. (2021)
	Unsupervised clustering (k-means, HMMs)	Player style profiling	Tactical archetypes	Vučković et al. (2014)
Sensors	Racket-mounted IMUs (Racketware)	Accel/gyro, ~500 Hz, shot summaries	Swing speed, impact detection	Racketware (2021)
	Wearable IMUs	Wrist/ankle/torso placement	Step/lunge analysis, workload indices	Brumann et al. (2021)
	Smart courts (interactiveSQUASH)	Cameras + pressure sensors + projectors	Live analytics, visual feedback	PSA & interactiveSQUASH (2018)
Comparative Tools	Tennis Hawk-Eye	Multi-camera triangulation, Kalman smoothing	Millimeter-level ball trajectories	Hawk-Eye Innovations (n.d.)
	Badminton shuttle tracking	High-fps cameras, motion-blur handling	Aerodynamic-aware trajectory models	Shuttle-tracking studies

Figure I. SUMMARY of EXISTING TECHNOLOGIES

VI. GAP ANALYSIS OF EXISTING TECHNOLOGIES

P. Limitations: Accuracy, Real-Time Data, and Scalability

Despite advances in image processing and machine learning, several limitations remain. In ball tracking, the squash ball's small size, rapid acceleration, and frequent occlusion often force algorithms to interpolate trajectories rather than measure them directly. Even high-performing systems such as Baclig et al.'s (2020) tracker produce frame-level errors that propagate into downstream metrics such as positional heatmaps and velocity estimates. Moreover, these models generally require controlled lighting and unobstructed views, conditions rarely met in community courts.

Real-time feedback is another critical challenge. Most pipelines process video offline due to the computational demands of deep learning inference and the need for temporal smoothing, resulting in latency that prevents in-game tactical adjustments.

Scalability also restricts adoption. Multi-camera rigs demand extensive calibration, synchronization, and data storage, making them viable for elite tournaments but impractical for most clubs. This disparity widens the gap between professional and grassroots squash.

Machine learning systems inherit similar constraints. Predictive models require large, annotated datasets, yet most squash datasets are either limited in size or proprietary. Consequently, models trained in one context (e.g., elite matches) often underperform when applied across different player levels, genders, or age groups.

Sensor technologies present additional trade-offs. Racket-mounted IMUs can quantify swing metrics but frequently misclassify shot types with similar kinematics (e.g., forehand drive vs. volley). Wearable IMUs measure workload but lack tactical context, while smart-court prototypes suffer from calibration drift and environmental noise.

Overall, current systems are more suited to controlled demonstrations or retrospective analytics than to robust, real-time coaching support.

Q. Missing Features: Lack of Integration Across Movement, Ball, and Player Analysis

A consistent limitation across existing systems is fragmentation. Image processing tracks spatial features such as player positions and ball bounces, sensors capture biomechanical data, and machine learning models classify or predict events. However, these domains rarely converge into an integrated framework.

For example, ball-tracking systems estimate bounce positions but cannot link them to biomechanics, while racket sensors quantify swing velocity without situating that action within tactical context. Coaches, however, require synthesis—connecting *how* a shot was executed with *why* it was chosen and *how* it influenced rally momentum.

Other racket sports illustrate the potential of integration. Tennis's Hawk-Eye simultaneously provides ball trajectories, player movements, and shot classification, creating a holistic tactical record. Squash, by contrast, lacks unified platforms. The absence of integrated datasets prevents advanced analyses, such as correlating biomechanical workload with tactical decisions or linking fatigue with error patterns.

This highlights a pressing need for technologies capable of fusing visual, sensor, and predictive data streams into a coherent analytic ecosystem.

R. Usability Issues: Complexity, Cost, and Adoption

Even when technically effective, many systems face usability barriers. Image-based systems often require complex calibration, while machine learning outputs may appear as "black boxes" with limited interpretability for coaches.

Cost is another constraint. Interactive systems such as interactiveSQUASH require permanent court modifications and substantial investment, while even more accessible solutions (e.g., racket sensors) can become cost-prohibitive when scaled across teams. This restricts access largely to elite players, raising equity concerns for junior, para-athletes, and low-resource communities.

Adoption is further influenced by cultural factors. Many coaches rely on experiential judgment and may view technology as intrusive or redundant without clear validation of performance benefits. Players, similarly, may resist systems that disrupt training flow or generate excessive data rather than actionable insights.

Thus, beyond technical barriers, practical alignment with coaching culture, resource availability, and user experience remains essential for successful implementation.

VII. WHY NO INTEGRATED SYSTEM EXISTS YET: TECHNICAL, ECONOMIC, AND DESIGN CONSTRAINTS

The absence of a fully integrated squash analytics system, comparable to tennis's Hawk-Eye, can be explained by converging technical, economic, and design barriers.

Technically, squash presents challenges that exceed those of open-court sports. The enclosed four-wall court generates frequent occlusions, reflections, and lighting inconsistencies, complicating video-based tracking. The ball's small size, high velocity, and low visual contrast demand more computationally intensive models than those typically required in tennis or badminton. Multimodal fusion remains underdeveloped: synchronizing video, sensor, and audio data is hindered by sampling discrepancies and synchronization drift.

Economically, squash represents a comparatively niche market. The smaller global player base and commercial footprint reduce incentives for large-scale investment. As a result, solutions such as interactiveSQUASH or Racketware emerge from small, independent firms with limited resources, restricting both scalability and long-term robustness.

From a design perspective, existing tools have largely been developed in isolation. Proprietary architectures frequently silo data, preventing interoperability and integration. Academic prototypes, while often innovative, remain experimental and rarely transition into sustainable commercial applications.

These combined constraints explain why squash technologies remain fragmented, valuable within their domains but collectively unable to deliver comprehensive, real-time, and widely adopted performance systems.

VIII. PROPOSED CONCEPT: AUTOMATED SQUASH TRAINING COURT (ASTC)

To address these deficits, this paper conceptualizes an **Automated Squash Training Court (ASTC)**: an integrated environment in which visual, sensor, and algorithmic technologies operate in tandem to generate holistic performance analysis. The design envisions a training ecosystem where multimodal data streams are synchronized, fused, and interpreted to produce actionable feedback for both players and coaches.

S. Conceptual Design

The ASTC recognizes that squash presents a uniquely challenging environment, with frequent occlusion, rapid ball velocities (often exceeding 270 km/h at elite level), and enclosed lighting conditions. To mitigate these constraints, the system is designed around multimodal capture rather than reliance on any single modality.

A distributed **camera array** forms the visual backbone. Ceiling-mounted panoramic units capture global player positioning, while high-speed corner cameras provide fine-resolution ball trajectories. Multiple perspectives reduce occlusion risk and ensure continuity of tracking.

The court itself functions as an additional sensing platform. **Embedded floor sensors** detect footfalls with millisecond resolution, recording recovery patterns and acceleration. **Impact-sensitive wall panels** capture precise ball–wall contact points and force, supporting trajectory reconstruction when video tracking is unreliable.

Complementary **racket-mounted IMUs** record swing mechanics such as velocity, orientation, and impact timing. Unlike full-body wearables, this minimally intrusive solution provides key biomechanical data without overburdening players.

All streams converge in a central computational engine. Convolutional neural networks process video for player skeletons and ball positions, while recurrent models (e.g., LSTMs) interpret sequences as rallies. Timestamp alignment enables cross-modal integration, linking swing mechanics, movement patterns, and tactical outcomes into coherent performance narratives.

T. Complementarity of Technologies

The innovation of the ASTC lies not in any single subsystem but in their orchestration. Each modality addresses the weaknesses of the others. Cameras provide spatial awareness but are limited by occlusion and motion blur; floor and wall sensors ensure continuity when visual tracking fails.

IMUs capture stroke dynamics but gain tactical relevance only when contextualized within rally flow. Machine learning serves as the integrative layer, harmonizing heterogeneous inputs into unified, interpretable patterns.

For example, when video loses the ball due to blur, wall sensors provide impact data that allow trajectory reconstruction. When a racket accelerometer registers high swing velocity, video and rally context determine whether this produced an effective winner or an error. By synthesizing across modalities, the ASTC potentially enables analyses such as identifying fatigue-induced errors, correlating recovery speed with rally outcomes, or quantifying tactical risk–reward trade-offs.

U. User Experience

Adoption depends not only on technical feasibility but also on user-centered design. The ASTC envisions distinct interfaces for coaches and players.

- **Coaches** access a dashboard aggregating performance over drills, matches, or training blocks. Visualizations such as heatmaps, rally flow diagrams, and tactical efficiency indices enable evidence-based evaluations. Crucially, the system emphasizes interpretability, highlighting causal contributors (e.g., late preparation preceding cross-court errors) rather than presenting opaque model outputs.
- **Players** receive simplified, motivational feedback via mobile applications or real-time projections. Post-session summaries highlight trends (e.g., "average rally duration increased by 12% with fewer unforced forehand errors"), while practice projections reinforce positional awareness.

By tailoring outputs to different users, the ASTC seeks to reduce cognitive load while maintaining analytical rigor. Longitudinal storage of multimodal data further supports athlete development, enabling coaches to monitor biomechanical, tactical, and endurance changes over extended periods.

IX. FEASIBILITY AND FUTURE CONSIDERATIONS

The Automated Squash Training Court (ASTC) offers a conceptual framework that addresses key deficiencies in current squash analytics, particularly fragmentation, lack of real-time feedback, and usability challenges. However, while the design potentially enables advances in accuracy, integration, and accessibility, its feasibility is constrained by unresolved technical, economic, and cultural factors.

V. Technical Challenges

The foremost technical barrier lies in **multimodal data fusion**. Aligning video feeds, floor sensors, racket-based IMUs, and wall impact panels requires synchronization at the millisecond scale. Without seamless integration, inconsistencies across modalities risk introducing new errors rather than eliminating existing ones. Even advanced systems in better-resourced sports, such as tennis, continue to face challenges in achieving robust, real-time multimodal synchronization.

Latency remains another critical issue. For the ASTC to provide tactical feedback within training sessions or near real-time post-rally analysis, the computational pipeline must be both high-throughput and low-delay. Squash's fast ball velocities and frequent occlusions demand high-performance processing. While cloud computing could enable scalability, data transfer introduces additional latency. An effective balance between on-site (edge) processing and cloud analytics will be essential.

Data availability also constrains feasibility. Current squash-specific datasets are limited, often proprietary, and lack diversity across playing levels, genders, and tactical situations. Training robust machine learning models requires large, annotated datasets; without this foundation, algorithmic accuracy will remain brittle.

Finally, hardware reliability must be ensured. Floor and wall sensors must withstand repeated high-intensity impacts and environmental stresses, while calibration routines need to run automatically to maintain validity across sessions. Hardware durability remains an underexplored challenge in sports technology deployment.

W. Economic Considerations and Accessibility

The squash market is comparatively small, limiting commercial incentives for large-scale investment. Implementing the ASTC would require significant upfront costs for cameras, sensors, computational infrastructure, and software development. For context, commercial systems such as **interactiveSQUASH** already demand permanent court modifications and high installation fees, restricting adoption to select clubs and academies. Similarly, **Racketware** sensors have gained traction only in niche segments, illustrating the difficulty of achieving scale without institutional backing.

Accessibility therefore becomes a central concern. If only elite facilities can afford advanced systems, the ASTC risks reinforcing inequalities in the sport. Scalable adoption may depend on **tiered deployment models**:

- *Short-term*: single-camera and low-cost IMU systems for grassroots coaching.
- *Mid-term*: hybrid camera–sensor prototypes deployed in regional academies for validation.
- *Long-term*: full multimodal ASTC installations supported by federations and professional tournaments.

Subscription-based analytics platforms could further distribute costs by reducing hardware dependence and shifting computational loads to shared cloud resources. Additionally, **federation-level support** may be critical, as demonstrated by Hawk-Eye's integration into professional tennis through endorsement by governing bodies.

X. Adoption and Cultural Factors

Even if technically feasible and economically viable, adoption depends on cultural acceptance by coaches and players. Squash retains a strong tradition of **experiential coaching and athlete intuition**, and technologies perceived as intrusive or opaque may be resisted. To address this, the ASTC must prioritize **explainability**, demonstrating *why* a recommendation is made by linking outcomes to clear biomechanical and tactical indicators.

Furthermore, institutional inertia is a significant barrier. Unlike tennis, which has normalized line-calling and broadcast technologies, squash has historically lagged in adopting performance technologies. Overcoming this resistance will require **pilot studies and longitudinal trials** demonstrating measurable performance benefits. Advocacy from governing bodies and integration into coaching education could accelerate cultural acceptance.

X. ROADMAP FOR DEVELOPMENT

1. **Short-term (1–3 years):**
   - Expansion of squash-specific open datasets for training robust machine learning models.
   - Development of low-cost, single-modality systems (e.g., camera-only or IMU-only) for grassroots use.
   - Initial pilot studies in controlled environments to evaluate technical feasibility.
2. **Mid-term (3–6 years):**
   - Deployment of hybrid camera–sensor systems in elite academies.
   - Validation studies assessing impact on player performance, injury prevention, and tactical development.
   - Development of coach- and player-facing interfaces with emphasis on explainability.
3. **Long-term (6–10 years):**
   - Full ASTC implementations in national training centers and professional events.
   - Federation endorsement to standardize analytics workflows across competitive levels.
   - Scaled-down modular versions for community clubs, leveraging economies of scale.

XI. CONCLUSION

This paper examined the technological landscape of squash training, highlighting key limitations that prevent existing systems from providing comprehensive, reliable, and accessible support. While advances in ball tracking, stroke recognition, and wearable monitoring exist, current tools remain fragmented and fail to integrate movement, tactical, and contextual data into a unified ecosystem. The main gaps identified include limited real-time accuracy, lack of integration across ball, player, and tactical dimensions, high complexity and cost, and low trust among coaches and players due to insufficient explainability and validation. These barriers explain why squash has not reached the level of technological adoption seen in sports like tennis or badminton.

The Automated Squash Training Court (ASTC) is presented as a conceptual blueprint to address these systemic shortcomings. By combining multimodal inputs—video, sensors, and machine learning—the ASTC envisions overcoming fragmentation, enhancing contextual feedback, and broadening accessibility, while complementing coaching expertise rather than replacing it.

The contribution of this paper lies in critically mapping the strengths and weaknesses of current technologies and proposing conditions for an integrated system to emerge. Future work should focus on developing datasets, conducting pilot testing, and involving federations to validate and refine such holistic training ecosystems.

In conclusion, advancing squash training requires moving beyond incremental improvements to isolated tools toward creating integrated, player-centered systems. This paper lays the analytical groundwork and provides a conceptual framework to guide researchers and practitioners in realizing that vision.

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