Understanding and Designing a Gaze-Based Interface for Table Tennis

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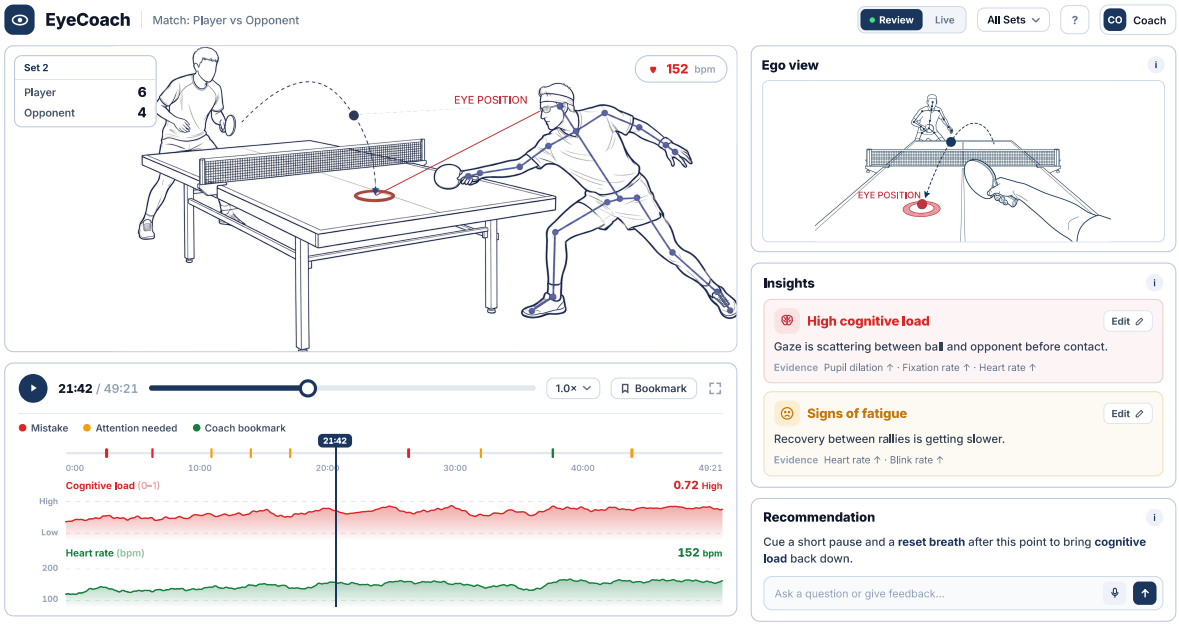

Figure 1: Envisioned design of EyeCoach, a multimodal system that uses gaze, pupil, heart rate, and pose to infer states such as cognitive load and fatigue. It gives real-time insights and supports post-hoc reflection, where coaches inspect explanations and give corrective feedback to personalise the model. Some elements were drafted using generative AI and edited by the authors.

Abstract

In fast precision sports such as table tennis, how players allocate their visual attention is an important indicator of performance. However, gaze data is difficult to interpret in real-world training settings, where eye, head, body, and scene motion make gaze signals noisy and highly context-dependent, and many existing methods are designed for controlled, offline analysis. Rather than expecting

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perfect predictions, we examine how gaze and multimodal sensing can support explanation, correction, personalisation, and improvement over time through a coach-facing system. To ground this design, we conducted semi-structured interviews with a coach and three table tennis players to understand their training routines and needs. The findings show that feedback should be tied to critical moments in play, combined with additional signals, translated into actionable guidance, and supported by clear explanations. Based on these insights, we propose EyeCoach, an Intelligent User Interface concept for personalised multimodal training feedback.

CCS Concepts

• **Human-centered computing** → **Interaction design process and methods**; **Interaction techniques**; **Interactive systems and tools**; • **Computing methodologies** → *Machine learning*.

Keywords

Eye Tracking, Intelligent User Interface, Human-in-the-Loop, Sport Training, Table Tennis

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1 Introduction

Eye tracking records eye movements and gaze locations over time [7], and is widely used to study what people focus on and how their visual behaviour changes during interaction [14, 17, 32]. Gaze and pupil measures have also been used as passive signals for modelling cognitive and behavioural states, such as confusion [27, 39, 40, 43], cognitive workload [26], stress [23], and emotion recognition [1, 8, 19, 45]. Unlike active gaze interaction, where gaze directly controls a system, passive gaze sensing treats gaze as a behavioural cue for interpreting the user's state or activity, often inferred using machine learning (ML) [10, 38].

Sport is a useful domain for passive gaze-based research because visual behaviour is closely tied to perception and action, as athletes must read fast-changing scenes, anticipate events, and prepare actions under time pressure [2, 5, 18, 25]. Prior work links gaze behaviour to expertise, visual search, decision making, and action preparation [2, 18, 25], with skilled performers often showing more task-relevant and temporally coordinated gaze, such as steadier gaze patterns [20, 36, 46]. Table tennis is especially relevant for studying gaze in sport, as it is a fast, dynamic visuomotor sport played under severe temporal constraints [16]. It also takes place in a constrained space where task-relevant elements stay visually central, and head-mounted eye trackers can usually be worn without obstructing the athlete's view. Prior table tennis studies have examined player behaviour and expertise-related differences [16, 34, 41, 42]. Recently, there has been a general shift in sport studies to use head-mounted eye tracking in realistic sporting environments [25, 37, 44], since gaze must be interpreted within the task context in which it occurs rather than as an isolated measure [5, 25].

However, turning gaze-based sensing into useful support for sport is a contextual challenge as much as a technical one. It requires identifying the needs of coaches and athletes, such as which signals matter, how and when feedback should be delivered, and how systems fit into existing training routines [42, 44], as echoed in broader sport research [12]. Head-mounted eye tracking in realistic settings also remains difficult, because continuous eye, head, body, and scene motion complicate analysis, and methods developed for static or screen-based settings do not transfer easily to mobile setups [9, 24, 28, 35]. In addition, real-time inference is a further challenge, as most work has focused on offline analysis and rarely addressed issues concerning latency, throughput, and hardware constraints [32].

Therefore, gaze-based sport systems need methods and interfaces that support the interpretation, refinement, and use of imperfect model outputs. One option is to frame them within interactive machine learning (IML) and intelligent user interface (IUI) approaches. IML lets users give feedback, correct outputs, and steer model behaviour over time [3, 11, 13], while IUIs use models of the user, task, and context to guide system behaviour [30]. Rather than expecting perfect predictions of states such as attention or fatigue, such systems could help coaches review gaze data in context, correct inaccurate labels, adjust which sensing modalities are used, and personalise feedback to the athlete and training goal.

Using table tennis as a concrete case, we conducted semi-structured interviews with four stakeholders (one coach and three players) to understand how they reflect on performance, which cues they focus on, and whether they see eye tracking as useful. Although we began with gaze, the interviews indicated that gaze alone was not enough and that additional signals could give a richer training context. Therefore, we frame the proposed system as multimodal, combining gaze, pupil data, heart rate, and pose estimation. From these interviews, we identify stakeholder needs and concerns, derive early design requirements, and outline an initial system concept and evaluation plan for how gaze and multimodal sensing could support table tennis training, contributing to the broader vision of interactive IUIs in sports.

2 Methodology

We conducted four semi-structured interviews with table tennis stakeholders after receiving ethical approval from the DFKI Ethics Review Board[1]. Given the small sample, we use the interviews as an early design step to inform the development of a gaze-based IUI training system, rather than a full qualitative account of table tennis practice. We selected participants to capture diverse perspectives on training, feedback, and technology use across coaching and playing roles, and experience levels. We report participants' technical backgrounds because these may shape how they think about model transparency, trust, and system feedback. The interviews and primary analysis were conducted by the first author, and the findings were then discussed and prepared by the author group.

Together, our participants offered different perspectives on gaze-based feedback across coaching and playing roles, more structured

[1] https://www.dfki.de/en/web/about-us/governance/ethics-team (Accessed 30 July 2026)

and more recreational backgrounds, and both technically informed and non-technical views, as follows:

C1 A highly experienced table tennis coach and former player, with over 50 years of involvement in the sport.
P1 A club player with 18 years of table tennis experience, including regular weekly club training.
P2 A former school- and club-level player with around 10 years of table tennis experience (including 4-5 training sessions per week), who no longer plays regularly. **P2** had prior experience with eye tracking and ML, which is relevant when interpreting comments on sensing, explainability, and system feedback.
P3 A recreational player with 20 years of intermittent, primarily self-taught table tennis experience, as well as experience in other ball sports, including cricket, volleyball, basketball, and tennis. **P3** also had prior experience in ML, which is relevant when interpreting comments on transparency, trust, and adaptation.

2.1 Interview Procedure

The interviews followed a semi-structured format and lasted approximately 30 minutes each. After obtaining signed consent, we began with background questions about participants' experience, playing level, and how often they play, then asked how they currently reflect on performance during or after practice, including what they focus on when playing well, what they notice when it drops, and which cues they already use. This first part focused on existing practice before introducing any sensing or system concepts.

We then discussed the role of eye movements and visual attention, including whether participants considered them important and whether they reflected on, monitored, or trained them, encouraging participants to elaborate freely with follow-up questions. Only then did we introduce eye tracking as a tool for training analysis, explaining that it could monitor a player's gaze over time and presenting common visualisations such as heatmaps to ground the discussion. We asked how such feedback would fit with existing practice, whether it might create practical challenges, and whether participants recorded signals (e.g., through wearables such as smartwatches) and how they used them. Finally, we discussed future uses of gaze-based and multimodal feedback, including ML-based analysis, trust in model outputs, real-time versus post-session use, and practical considerations such as comfort, wearability, and intrusiveness.

2.2 Analysis

We conducted a small-scale analysis of how participants reflect on performance and visual attention, and identified early design requirements for gaze-based and multimodal ML support. After each interview, the first author wrote brief reflection notes on initial observations, participant-specific context, and salient issues. The interviews were then transcribed or written up from notes, then anonymised and summarised per participant. The first author read the transcripts, notes, and summaries to identify recurring topics within and across interviews, such as how participants reflect on performance, how they understand visual attention and player state, how eye tracking, multimodal sensing, and ML-based feedback might fit into training, and recurring concerns about actionable recommendations, trust, explanations, personalisation, and practical constraints such as sensor comfort. We then compared and grouped these themes across participants, checking them against the summaries and original material. Given the small sample, we present the findings as early design insights rather than generalisable claims about table tennis players or coaches.

3 Findings

Performance cues. Participants interpreted performance through multiple cues rather than a single signal. **C1** distinguished technical, tactical, and behavioural aspects of play, arguing that correct stroke execution is not enough if the tactics are poor or the player is struggling under pressure, and described table tennis as a "mind game" in which focus, nervousness, fatigue, and body language shape how players perform and how coaches intervene. **P1** and **P3** saw reflection as socially mediated, relying on teammates to spot issues that are hard to notice alone, such as incorrect stroke execution, while also stressing timing and mental states like concentration and nervousness. **P2** and **P3** similarly linked performance to posture, risk-taking, opponent pressure, and mental state. Therefore, reflection in table tennis already combines visible movement, game context, and behavioural interpretation, and is often done in groups rather than focused on isolated technical performance.

Attention in context. Participants treated visual attention as important but not meaningful in isolation. **C1** described explicit drills for concentration and attention, including dual-task and colour-based reaction training, so attention is already trained as part of broader practice. **P3** saw it as important but mostly implicit, something players rely on without reflecting on directly, and **P2** recalled being told to watch the ball and anticipate the opponent, noting that coaches can observe head but not eye movement. Gaze feedback was thus valued mainly when tied to specific moments. **P2** was cautious about broad gaze visualisations, arguing that what matters is whether the player looked at the right place "at the exact moment", not where attention was distributed overall. **P3** valued replay review for revisiting moments where they lost track of a fast ball and for inspecting positioning and how the opponent played different balls. Gaze became meaningful when linked to concrete moments of action rather than treated as a standalone measure.

Action over detection. Feedback was seen as useful only when it helps the player or coach act. **C1** was clear that detecting stress or loss of focus is not enough without a concrete response, such as a breathing cue or a tactical adjustment usable in the moment. **P1** agreed that passive signals help only if they show the player how to behave and overcome a problem, not if they only report that something is wrong. **P2** put this most directly: "if the system tells me that you're nervous, I would be more nervous"; for **P2**, labelling a state could be counterproductive unless the feedback also indicates what to focus on or how to react. **P3** preferred small in-play recommendations, such as adjusting position, watching the bounce, or changing shot selection. The value of sensing was tied less to detection than to whether it could support practical action.

Timing of support. Participants differed on when feedback should arrive. **C1** strongly valued real-time support, since coaches must intervene when a player becomes unfocused or unstable, for

example, by reading body language, calling a timeout, or prompting the player to refocus, especially under the pressure of competitive matches. **P2** also preferred real-time feedback, arguing that table tennis needs immediate reaction and is most useful while the player can still adjust. **P1**, by contrast, emphasised post-session reflection to improve for the next match, and **P3** leaned the same way because the game is fast and short, though **P3** still valued subtle real-time cues if they were easy to act on.

Acceptance of multimodal sensing. Participants were generally open to sensing modalities. **C1** was open to eye tracking and heart rate, provided they gave interpretable, actionable support rather than measurements alone, and noted that heart rate was already common and useful. **P1** was the strongest supporter of multimodality, arguing that more signals give more insight, and pointed to heart rate and posture tracking alongside eye tracking. **P2** suggested combining gaze with acceleration, gyroscope data, movement speed, gaze-movement synchronisation, heart rate, and pose, linking these to reaction speed and coordination. **P3** would wear such devices only when unobtrusive and not distracting. Multimodal sensing was seen as useful if it offered richer insight without obstructing performance.

Trust and personalisation. When asked about ML-based systems, participants were generally open, but only if accompanied by transparency, practical usefulness, and visible improvement over time. **C1** and **P1** both stressed understanding what happens behind a decision. **C1** would use ML as long as it explains why it reached its prediction, which signals contributed, and how the output helps the player, adding that performance analysis is already common in table tennis, so an ML layer felt acceptable. **P1** wanted to see "behind the curtain", **P2** valued explanations for judging whether the system was on the right track, and **P3** likewise wanted to know how it reached a conclusion. These views also shaped error tolerance and personalisation, i.e., **C1**, **P1**, and **P2** would tolerate some mistakes if the system could explain itself, improve, and adapt to the individual player. **P1** was clearest on this, stating "No, I want a system [that is] tailored to me, which is better." **P3** judged trust more practically, by whether the system gave more useful than unhelpful feedback and adapted to their style. Participants were willing to engage with ML if it remained interpretable, useful, and responsive, but were unlikely to continue using one that was hard to understand, rigid, or repeatedly wrong.

4 Discussion and System Design

Our findings suggest that gaze-based feedback is unlikely to be useful as a standalone detection system. Although we began with gaze, participants pointed to additional signals that could give richer context, and stressed actionable feedback for adjusting behaviour in real time or for future play. Therefore, we propose EyeCoach, a multimodal IUI coaching system for player monitoring (Figure 1) that combines gaze, pupil data, heart rate, and IMU-based pose estimation to infer relevant behavioural states and provide cues to players. In a first version, it targets cognitive load, which may reflect moments of increased task demand, attentional strain, or uncertainty during practice [31]. We will use gaze, pupil, and heart rate features to detect cognitive load, with heart rate also feeding later models for fatigue [21, 22]. The planned setup uses a 200 Hz head-mounted eye tracker from Pupil Labs[2], the Polar H10 Heart Rate Sensor[3], and possibly the QSense Motion 9DOF IMU Sensor Kit[4]. This reflects participants' interest in richer sensing while respecting their concern that devices should not obstruct play. We may draw on datasets such as CLARE [6] to inform initial feature and modelling choices, before collecting table-tennis-specific data for evaluation and personalisation.

EyeCoach includes real-time and post-hoc views. **The real-time view** is intended mainly for coaches during play, showing gaze, visual attention, pose, and passive state monitoring. State-based feedback appears only when the model is sufficiently confident, alongside a short, actionable cue such as "Take a breath and refocus" for high cognitive load. When the model is uncertain, it avoids potentially misleading labels and shows only the monitoring views. This responds directly to participants' concern that labelling a player as nervous or unfocused may be unhelpful, or even counterproductive, unless the feedback is reliable and actionable, and it supports coaches in reading the player's state and deciding on interventions. **The post-hoc view** supports reflective analysis by players and coaches. Users can replay match segments, inspect predicted states on a timeline, review model confidence, and see why a prediction was made. It can show gaze visualisations, such as heatmaps for overall attentional distribution and scanpaths for temporal gaze transitions during replay. Users can compare the contribution of different modalities, toggle signals, correct labels, and use corrected examples to refine the model over time. Coaches can also edit which states or signal combinations trigger particular recommendations, keeping the system aligned with their practice.

For modelling, we begin with inherently interpretable classical models using extracted signal features, and use recent mobile eye-tracking methods for gaze event detection [9, 33]. For real-time inference, we plan to use rolling windows with synchronised multimodal features, accounting for differences in sampling rates across gaze, heart rate, and motion signals. We will first explore early fusion, combining features across modalities before classification. We report model confidence and provide simple textual explanations of which features contributed to each prediction, using SHAP-based feature importance [29] translated into short user-facing summaries. We start with generalised models, as these can perform well in noisy real-world physiological settings [4] while still supporting later personalisation through user correction and fine-tuning, consistent with work showing that classical models can outperform deep learning for cognitive load detection on small wearable datasets [15].

5 Conclusion and Future Work

We examined how gaze-based and multimodal feedback may support table tennis training. Through interviews with four coaches and players, we identified a need for feedback that is temporally grounded, actionable, explainable, personalised, and usable across both live and post-session training. Based on these findings, we

[2]https://pupil-labs.com/products/neon (Accessed 30 July 2026).
[3]https://www.polar.com/en/sensors/h10-heart-rate-sensor (Accessed 30 July 2026).
[4]https://qsense-motion.com/ (Accessed 30 July 2026).

proposed an IUI design that treats gaze data as evidence to be interpreted, questioned, and corrected rather than as an automated measure of performance.

Future work will prototype and evaluate EyeCoach in two stages. First, a formative prototype study in which coaches and players review segments of play using both views, examining whether the feedback, confidence information, explanations, and correction options are understandable and useful, to refine the interface and human-in-the-loop workflow. Second, a short exploratory study during practice, observing how coaches and players use, ignore, correct, or adapt the system outputs. We do not claim improvements in training or fully automated state detection at this stage; instead, we examine whether imperfect gaze-based and multimodal predictions can support reflection and coaching while users remain active in interpretation, correction, and personalisation.

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