Why Sports Needs Interactive Machine Learning

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Abstract

Sports technology generates vast amounts of rich data that could be processed via machine learning. Yet, traditional machine learning research often fails to deliver practical value for sports. In this essay, we argue that this is because sports practitioners have too little control over model behavior during development and use. As a solution, we present interactive machine learning (IML), where models and user interactions are developed together. Drawing on recent applications of IML in sports education, competitive athletics, and rehabilitation, we argue that IML can support AI technology that better integrates into sporting practice. We further emphasize that it requires close collaboration between artificial intelligence developers and domain experts. We call upon the SportsHCI community to facilitate this exchange. We provide actionable advice for SportsHCI researchers to pursue IML and highlight the significant research opportunities this presents.

CCS Concepts

• **Human-centered computing** → **Human computer interaction (HCI)**; • **Computing methodologies** → **Machine learning**.

Keywords

Human-in-the-loop, human-centered AI, interactive machine learning, sports analytics

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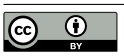
1 Introduction

Sports technology, such as body-worn sensors or egocentric and exocentric cameras, produces vast amounts of data that could support the decision-making of athletes, coaches, and other sports practitioners. For example, heart rate sensors can inform about athletes' exertion and stress levels [5, 41], IMUs can help diagnose body posture and technique [10, 49], and camera tracking can support teams in reviewing tactics and coordination [52]. Machine learning (ML) has emerged as an effective way to process such large amounts of data. It has created meaningful data representations in challenging and complex environments ranging from medicine [32] to science [51], and has been discussed as a promising way to facilitate activities in sports [15]. However, despite some notable successes (e.g., [17, 29]) and many ML papers explicitly referring to sports as an application domain [23, 25, 39], sports practice is still slow to adopt ML technology. There appears to be a barrier that prevents advances in ML from transferring to sports practice. In this essay, we argue that this is because we are applying ML in sports the wrong way.

Looking at the intersection of ML and sports in artificial intelligence (AI), human-computer interaction, and sports literature, there is a fundamental mismatch in how sports are invoked by ML research and how sports practice is involved in the development of ML models and systems: AI research commonly discusses sports to motivate ML tasks or to speculate about potential downstream applications. However, it rarely engages with sports practice or involves sports practitioners in the design and development of actual ML solutions. For example, it may develop a prediction model for defensive team behavior in football by referring to its potential to support tactical planning without ever consulting actual football practitioners [29]. Athletes, coaches, and analysts, in turn, are generally optimistic about the potential of ML to support their needs and activities. But, in practice, they lack controls to steer and customize model behavior, particularly to adapt ML systems to individual athletes or environments [23]. There is a clear disconnect between the sports and ML communities that limits the utility of ML-based systems in sports and slows their adoption.

We argue that much closer collaboration between AI and ML developers and sports experts is required, reaching all the way to highly technical and architectural decisions. Sports practitioners must be able to shape how ML models behave in their own circumstances, including after deployment. We propose *interactive machine learning* (IML), a design and ML approach that focuses on the end-user's opportunities to shape and direct the behavior of ML models, as a concrete solution to this problem. It treats model development and user interaction as a joint design problem [27] and thus promotes deep collaboration between technical developers and domain experts to customize model behavior even after deployment. We argue that this approach creates a strong fit between ML technology and established sports practices and can produce more



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effective and personalized AI systems. We thus call upon the field to realize the opportunities of IML in sports and provide practical advice to foster adoption.

We present our argument in the following way: First, we illustrate how ML is usually applied to sports contexts and why traditional ML often fails to deliver value in practice. In traditional ML, models are trained primarily by technical experts on pre-defined data and objectives; sports practitioners are mainly consumers of outputs and do not actively shape model behavior. Then, we examine human-in-the-loop ML, where practitioners are more involved but remain limited in how they can shape model behavior. Here, practitioners contribute to training, validation, or decision-making, but usually within channels and roles defined in advance by the system designers. Finally, we present IML as an approach that centers interaction as a means to steer model behavior and discuss its implications for the SportsHCI community. In IML, practitioners iteratively inspect, contest, and steer model behavior based on their own situated concepts, cases, and performance criteria; model adaptation is a central part of the user interaction, not just a backend process. Drawing on case studies from sports education, competitive athletics, and rehabilitation, we show how IML contributes to AI technologies that support established sporting practices. We detail how IML requires close collaboration between AI researchers and sports practitioners and stress the role and responsibility of SportsHCI to facilitate this exchange. We conclude by highlighting opportunities where IML could support new sports contexts and contribute to a broader understanding of how to design useful AI, and provide practical advice for SportsHCI researchers looking to adopt IML for their use cases.

2 Traditional Machine Learning Research for Sports Neglects Sports Practice

Traditional ML research is by far the most dominant approach to developing and deploying AI technology in sports. It is conducted primarily—if not exclusively—by AI researchers using pre-defined datasets, model architectures, and/or training setups. It has produced models and systems that can process vast amounts of data and closely align with annotations from human observers [23, 25] in areas ranging from risk assessment [8] to performance and outcome prediction [8, 26] to sports analytics [19]. However, it has also repeatedly failed to deliver practical value to sports experts, stemming from a lack of inclusion of those sports domain experts in the AI development [23, 25].

2.1 How is traditional machine learning applied to sports?

Generally, applying a traditional ML approach to sports means that structured data (e.g., box scores, player statistics, or game results) and known algorithms (e.g., Random Forests, Logistic Regression, or XGBoost) are employed to predict outcomes or identify patterns. For example, AI researchers may focus on an established dataset of game and player statistics to predict game outcomes or point spreads, assuming that this outcome will be immediately relevant to sports applications such as betting markets [26]. Or, they may motivate a behavior prediction problem by referring to the reported practices of professional sports teams in reviewing and developing in-game tactics, using existing data to develop new models of team defense that could plausibly match and support those established practices [29].

From an interaction perspective, traditional ML places sports practitioners mainly in the role of consuming model outputs. Even when sports practice is invoked as a motivation, practitioners typically do not gain direct means to inspect, contest, or adapt how the model behaves in their own setting. The underlying assumption for such an approach is that solving the respective modeling problem through a more sophisticated or powerful AI technique will necessarily yield benefits to sports practice [27]. Typically, traditional ML work therefore does not involve any intended users, such as sports analysts or coaches, during model development or evaluation. Instead, it relies on data-centric evaluation strategies that report measures such as prediction accuracy or present select examples to illustrate plausible predictions [19]. The implicit argument is that the modeling problem is sufficiently well-defined and the data sufficiently representative that no further involvement of practitioners is necessary. The core limitation of traditional ML in sport is thus not simply low accuracy, but low practitioner control over model behavior, which produces tensions with the individuality and dynamics of the sports concepts to be modeled.

2.2 How does traditional machine learning fail to serve sports practice?

In select cases where concepts and conditions are sufficiently stable and understood, a traditional ML approach has delivered practical value to sports professionals, for example, in injury prevention [8] and refereeing [36]. It has, however, repeatedly failed to address the highly individual needs of sports practice [15], leading sports research to lament a general disconnect between the AI and sports communities [23, 25, 38, 39].

Over the past decade, evidence has begun to accumulate that ML and AI research is not sufficiently engaging with sports practice. Early reviews in professional sports have repeatedly found that practitioners, such as coaches or managers, cannot make use of the predictions of ML models developed by AI research in isolation. They lack guidance and explanations to make sense of the models' predictions and cannot adapt the models' behavior to their specific teams and players [23, 25, 38]. In elite sports in particular, traditional ML research has been critiqued for failing to consider the importance of the individuality of athletes and teams. Elite athletes are, by definition, outliers compared to the overall human population. The diverse profiles of athletes and teams thus require interaction between sports experts and AI to tailor a model's behavior to a particular individual or team context and achieve acceptance with the athletes and coaches [23]. These issues have been traced back to a failure among the AI researchers to pursue appropriate modeling objectives: While AI research focuses on statistical measures of accuracy and precision regardless of model structure, coaches and managers require traceable, adaptable, and causal predictors of performance that can yield practical insights for tactical decision-making [25].

Traditional ML research in sports has further been critiqued for highly favoring well-funded and already data-rich sports disciplines, such as football, American football, baseball, basketball, or

hockey, while neglecting smaller or niche sports where AI could have a strong impact, including Olympic disciplines [23]. This has, in part, been linked to a form of *hen-and-egg* problem: AI is primarily applied in areas where vast amounts of data already exist, thereby generating new funding for AI research. However, data is only produced where funding is already present to afford data collection in the first place [23]. Sports research has thus commonly called for more collaboration and exchange across the AI and sports disciplines, as well as a greater inclusion of sports experts in the development of AI technology to broadly deliver value across areas of sports and sports disciplines [23, 25, 38].

Overall, sports research and practice have expressed discontent that traditional ML research has repeatedly failed to provide tools that are sufficiently rooted in decision-making practices in sports and that are interactive, transparent, and inclusive enough to be practically useful.

3 Human-in-the-Loop Machine Learning Is a Start But Not Enough

To address these issues, some AI research has begun to include sports domain experts in the ML loop under the name *human-in-the-loop machine learning*. These may be athletes, coaches, or managers, but also analysts [40], trainers [31], physiotherapists [48], or educators [13, 56]. How those experts are included in the ML loop can vary. They may contribute to training, validation, or decision support, but usually within interaction channels and roles defined in advance by the system designers. For example, experts may be included in the model training by labeling data where the ML model is uncertain, constituting forms of interactive labeling [9], active learning [1], or human-in-the-loop optimization [11]. Alternatively, the AI system may include a decision-support or recommender component [31, 40, 53], aiming to reduce the load of the sports domain expert by providing assistance in their decision-making.

3.1 How is human-in-the-loop machine learning applied to sports?

Human-in-the-loop approaches recognize the importance of expertise in sports decision-making to deal with uncertainty and ambiguity. Even if the goal is to eventually achieve full automation, this research thus designs AI technology as tools to facilitate and scale the expertise of the sports practitioner. In general, applying human-in-the-loop ML in sports contexts means integrating the domain knowledge of sports experts (e.g., athletes, coaches, or scouts) directly into the ML pipeline to refine predictions and handle nuances that raw data alone might miss.

A prime example for a human-in-the-loop system in sports ML is Mahyari *et al.*'s [31] recommender system for physical exercises: Mahyari *et al.* were concerned with the challenge of applying a recommender systems approach to exercises and workouts, where data is limited compared to traditional application areas of recommender systems, such as media streaming or e-commerce websites. To overcome the cold start problem, where informative data about a new user is lacking at the time of sign-up, and there is general uncertainty about appropriate exercises for the user, they therefore included personal trainers in the ML loop. When the learning model indicated high levels of uncertainty about its recommendations, for example, when a new user signed up, or many exercises were considered equally likely to be fitting, the trainers manually provided exercise recommendations. This helped deliver appropriate exercises to the end-user. At the same time, it built up a high-quality dataset for later recommendations. Through this process, the model achieved higher levels of accuracy than fully automated systems. It also allowed the personal trainers to serve many more clients than with manual recommendations alone.

While Mahyari *et al.*'s recommender system still strongly emphasizes automation and focuses on data collection and model training, the class of human-in-the-loop systems called decision-support systems is commonly more concerned with the outputs of fixed ML models that should facilitate decision-making practice. A great example for such a system is Seidl *et al.*'s [40] *Bhostgusters*: It lets professional basketball coaches dynamically interact with a prediction model for individual and team defensive behavior. Using a tablet application, basketball experts can use familiar notation schemes (e.g., wavy, dashed, and dotted arrows to represent dribbling, passing, and shooting) to sketch offensive team behavior. They can then interactively explore counterfactual *"what if?"* scenarios for defensive reactions provided by the model. This amplifies the coaches' ability to make real-time, courtside tactical decisions using familiar tools and processes. Seidl *et al.*'s work closely resembles and directly builds on work by Le *et al.* [29], who followed a traditional ML approach to develop a prediction model of defensive team behavior in football. While Le *et al.*'s work is mainly concerned with the technical feasibility and performance of the developed model, Seidl *et al.* spend considerable effort to understand and support the decision-making practices of coaches and analysts.

Other works that similarly include sports domain experts in the ML loop are the annotation-support systems by Ai *et al.* [1] for basketball analysts and by Deng *et al.* [9] for table tennis and racket sports. These works, similarly, take both the user interaction and the model's performance into account, as well as their interplay [27], to integrate AI and ML systems into practical sports processes.

3.2 What is the problem with most human-in-the-loop machine learning?

Human-in-the-loop ML changes who participates in the pipeline, but not necessarily who controls model behavior. While human-in-the-loop ML is necessarily more concerned with sports practitioners and practice, many forms of human-in-the-loop ML still put considerable agency in the hands of the system rather than the practitioner. In many such systems, sports practitioners contribute valuable expertise through roles defined in advance by the system, for example by providing labels, recommendations, or choices among model-generated options. These roles can improve model performance and practical fit, yet they often stop short of allowing practitioners to redirect the model according to their own situated concepts and criteria. What is missing is not human input as such, but an interaction loop through which practitioners can repeatedly inspect, contest, and redirect model behavior in relation to their own goals. For example, if a system ultimately decides which samples will need to be labeled and how, the domain experts are reduced to simple oracles that could be replaced by any other black-box function [2]. Even further, if the domain experts have no

meaningful way to affect model behavior, they are severely limited in the ways they can tailor the systems to their needs. Setups like those force the practitioner to adapt to the system, rather than the other way around, and ultimately limit the flexibility and utility of those systems in practice.

To illustrate this, we can return to the example above: While Seidl *et al.*'s [40] human-in-the-loop system lets coaches explore alternative team tactics, it stops short of letting sports experts influence the model's predictions themselves. If, for example, the predicted defensive behavior were to severely violate the expertise of a sports analyst or professional coach, such as when defensive coverage in the respective sport had shifted or differed for a specific team, it would not offer a way to adjust the predictions. Similarly, if a specific defensive behavior was not represented in the training data, it could not offer any mechanisms to inform the model of these shortcomings and recover its utility.

Many human-in-the-loop systems thus still remain highly constrained to the stereotypes and abstractions of user needs that were considered at design time. They fail to provide the necessary flexibility and controls that will allow sports practitioners to truly tailor their systems to their circumstances and needs, especially if those circumstances are highly unique or change over time.

4 The Case for Interactive Machine Learning

In our opinion, interactive machine learning (IML) stands out among the human-in-the-loop approaches as engaging most immediately with the established practices surrounding sports activities. It enables sports experts to directly interact with the underlying ML model, taking the initiative to steer and shape its behavior [12]. This allows experts to customize and tailor the model to their specific practice and decision-making context. We thus argue that it represents a direct answer to sports practitioners' needs for more interactive and personalized AI systems [23].

4.1 What is interactive machine learning?

IML describes a process in which a user or user group builds an ML model through iterations of input and review [12]. This includes activities such as supplying or correcting training data, adjusting features, feature importance, and model structure, as well as reviewing model outputs and behavior [12] (see Figure 1). The term is commonly attributed to Fails and Olsen [16] who used it in the context of an image segmentation application where users repeatedly refined a model's foreground and background predictions by interactively "drawing" the correct label for an image area over the model's predictions. It was later popularized in the seminal *Power to the People* by Amershi *et al.* [2], who collected ML systems centered around the interaction with their users.

In IML, model refinement and user interaction are closely intertwined. It lets practitioners iteratively inspect, contest, and steer model behavior in relation to their own situated concepts, cases, and performance criteria. Model adaptation is therefore not just a backend process, but part of the user interaction itself. What distinguishes IML from broader human-in-the-loop approaches is the practitioner's role in the interaction. In contrast to most human-in-the-loop approaches, practitioners can explicitly shape the components and setup of the ML loop through appropriate interfaces to affect how the model behaves in relation to their own goals and concepts. The same underlying model family could thus support traditional ML, human-in-the-loop ML, or IML, depending on whether practitioners only receive predictions, annotate for system needs, or iteratively steer the model according to their own situated goals.

IML has been found to improve model effectiveness and usability compared to traditional ML methods, especially when data is sparse or heterogeneous [2]. It was further found to spur reflection, facilitating questions such as *"What constitutes good training data?"* or *"What are the key properties of my class of interest?"* with its users [56]. Research has also indicated that IML can facilitate trust calibration [30], communicating a model's capabilities as well as its limitations to its users, thus enabling a more effective integration into practical decision-making processes [21, 22, 47]. All these properties make IML highly relevant for AI applications in sports.

4.2 How is interactive machine learning applied to sports?

IML has just begun to be employed in sports, with emerging applications in athletic competition [34], rehabilitation [48], and education [13, 56]. These initial works show that IML can mitigate issues related to data scarcity and incorporate important contextual information to improve model accuracy and calibrate user trust. They underscore that IML warrants significantly more attention as an approach to AI for sports, but also raise new challenges. To show how IML can address the individuality of athletes and sports practice, we present those early IML case studies here in detail. We then highlight the pressing opportunities for future research that they indicate.

4.2.1 IML in athletic competition. To support Marathon coaches, Muijlwijk *et al.* [34] developed a system to estimate challenging race paces using a case-based reasoning approach [43]. Coaches could interactively set the input weights for previous races of the same athlete using a web-based interface, directly influencing and interactively exploring the model's predictions. In a qualitative and quantitative evaluation with practicing Marathon coaches, this interaction resulted in more accurate race-pace predictions than automatic predictions generated by the model alone. Coaches utilized contextual knowledge, such as a runner's injury history and personal circumstances, to adjust the model's predictions. The authors found evidence supporting a high chance of successful adoption, with their results indicating well-calibrated trust among the coaches. However, more experienced coaches displayed lower levels of acceptance, preferring to rely on their own experience rather than the model's predictions. Furthermore, the results indicated that generic domain expertise was not enough to fully leverage IML. When coaches used the model to predict race paces for unfamiliar runners, they heavily relied on the model's unmodified outputs, reducing the interaction to regular AI use.

4.2.2 IML in physiotherapy. To facilitate personalization, assessment, and communication in physiotherapy, Turmo Vidal *et al.* [48] devised a conceptual infrastructure for an IML system. Based on a Research through Design approach involving interviews, workshops, and technology explorations with physiotherapists and ML

experts, they proposed a looped model where therapists and patients co-train a movement classifier to capture patient rehabilitation and support the correct execution of prescribed exercises through personalized feedback. They identified that the primary benefit of IML in this context is solving the *hen-and-egg* problem of data scarcity since IML allows for the incremental creation of personalized models without requiring large, pre-existing datasets. This fosters a tight link between the individual patient and the model, ensuring the technology accommodates diverse bodies and ailments. However, they also noted that IML poses challenges regarding the users' control over the system, such as the need for easy-to-use tools for data editing or feature selection that integrate into established clinical workflows. They thus highlight the need for domain-specific interfaces to support the required expert steering, both by the physiotherapist and by the patient.

4.2.3 IML in education. To investigate the potential of IML to support ML literacy and creativity, Zimmermann-Niefield *et al.* [55, 56] developed a mobile ML application that let youth athletes train classifiers on their own physical movement data using wearable sensors. In a workshop setting, they observed that the students could successfully leverage their existing bodily knowledge to curate datasets and steer the model's behavior. The tight feedback loop of IML allowed participants to identify classification errors and immediately refine the training data to correct them. However, the authors also identified a significant tension between model performance and athletic realism. Participants tended to perform exaggerated or inauthentic movements to help the algorithm distinguish between 'good' and 'bad' techniques. This tendency resulted in models that were statistically reliable but failed to capture valid athletic practice, effectively forcing the user to adapt to the system's limitations rather than the reverse.

Similarly, Duval *et al.* [13] utilized IML to enable children, particularly those with Sensory-Based Motor Disorder, to design exergames using a design probe called *Cirkus*. The authors employed a participatory approach where children recorded their own movements to teach the system to recognize animal-themed exercises, for example, recognizing when a child 'walked like a bear', or 'jumped like a kangaroo.' This allowed the children to build bespoke movement classifiers through gameplay. They found that framing the model training as shepherding an incompetent agent (i.e., teaching the technology to recognize "correct" movement as defined by the children) motivated participants to engage in otherwise tedious repetition, solving the data scarcity issue common in movement-based AI without exhausting the users [20]. Furthermore, the participants retained agency over how their bodies were represented by the data and model. It allowed them to define their own correct movements rather than being measured against normative standards that would exclude users with impairments. However, the authors also noted that this open-ended, exploratory steering resulted in technically inaccurate models due to the heterogeneity of the input data. While they leveraged this inaccuracy as a playful antagonist in their specific context, they identified that their reliance on play to drive repetition challenges the generalizability of the approach.

4.3 How does interactive machine learning integrate with sports practice?

The case studies above show that, by letting experts steer the process, IML lets sports practitioners incorporate important contextual information into models to improve accuracy, calibrate user trust, and accommodate their unique circumstances. IML also mitigates issues related to data scarcity by engaging users directly in the training loop, thereby generating the necessary data. Through these processes, it empowers sports practitioners to build personalized tools that maintain their agency and support inclusivity.

However, this tight coupling between practitioners and system also introduces distinct tensions. The very interactions required for steering raise a practical design question: how much ongoing work can coaches, athletes, therapists, or analysts reasonably be expected to perform before steerability becomes an interaction burden? For some users, the potential utility of a custom estimator may not outweigh its expected costs. The observation by Muijlwijk *et al.* [34] that experienced marathon coaches did not change model settings seems to point in this direction. An additional major risk is that athletes may distort their actual technique to satisfy the model's mechanisms, forcing the user to adapt to the system rather than the other way around, a phenomenon corroborated by other AI work in sports [45]. Furthermore, the examples illustrate that interactive steering does not automatically guarantee accurate models or overcoming expert resistance. Effective use of IML in sports appears to require highly specific expertise regarding the data rather than just generic domain knowledge. Consequently, the success and adoption of IML in sports appears highly likely to depend on carefully designed interfaces that respect and integrate into the established sports practices of specific individual domain experts. Instead of solely focusing on model performance, close collaboration between ML experts and practitioners will be required to realize this vision.

5 The Role of SportsHCI

The SportsHCI community is uniquely positioned to facilitate the exchange between ML and sports experts required by IML. While ML researchers are rarely trained in designing for and with practitioners, sports experts rarely have the resources or training to develop ML systems by themselves. The SportsHCI community, on the other hand, already studies how users and sports technology interact. It has been at the forefront of identifying and communicating the needs and challenges of sports practitioners using interactive computing technology, including processing vast data using ML [15]. SportsHCI researchers are trained in user research *and* know how to develop technical systems. They have an opportunity—and we would argue a responsibility—to help create AI systems that promote practitioner steering, situated use, and integration with established sporting practice.

SportsHCI can build on a mature IML literature (e.g., [2, 12, 33]) and on existing ML and interface tooling to achieve this goal. There are, however, still open challenges that research applying IML to sports must address. Making modern deep learning models transparent and interactive is still very difficult. Many contemporary ML structures remain notoriously opaque and data-hungry. This presents a unique opportunity for future research. Resolving how to make complex ML interactive will not only push SportsHCI, but the

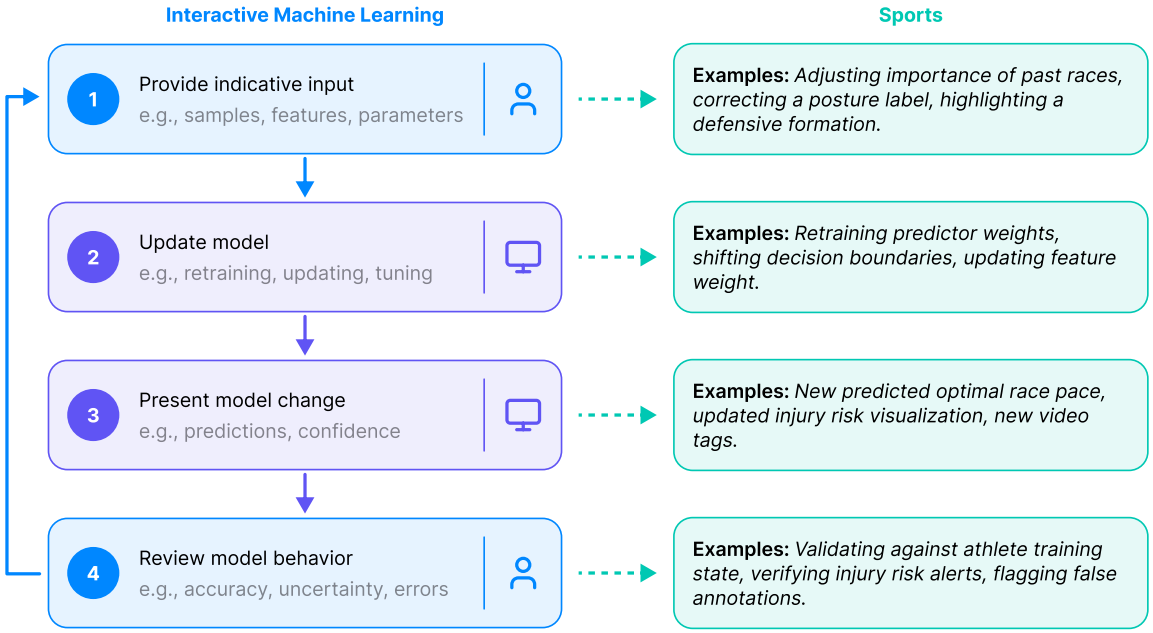

Figure 1: Interactive machine learning loop applied to sports. In the IML paradigm, domain experts (e.g., coaches, physiotherapists) steer the development of AI models to accommodate the personal and context-dependent nature of athletic performance. The loop begins with (1) the expert providing knowledge-rich input, such as identifying outlier performances or correcting motion labels. (2) The system updates the model and (3) visualizes the new behavior, for instance, by projecting a new race strategy or highlighting predicted injury risks. Finally, (4) the expert reviews the outputs against their professional judgment, for example, regarding an athlete's capabilities, to determine if further refinement is necessary.

entire field of ML forward. Sports offers a particularly demanding testbed here because relevant concepts are often individualized, embodied, and temporally unstable, shifting across athletes, teams, injuries, and competitive contexts. In the remainder of this section, we point out where and how SportsHCI can start to apply IML in sports, focusing on use cases where practitioners need to define, revise, and steer model behavior in relation to their own concepts.

5.1 Translating interactive machine learning to sports

Outside of sports, IML has been successfully applied in problem domains such as text processing, computer vision, and activity recognition [2, 12]. Across these applications, IML has offered domain experts tools to define and work with their own concepts, such as custom class definitions. These applications show that there is untapped potential for IML to benefit sports practice, allowing experts to use ML to process data for analysis based on their own conceptions (see Figure 1). These areas, like sports, require systems that accommodate expert-defined, context-sensitive, and revisable concepts. We highlight these areas here because we find them to map particularly strongly to activities in sports practice.

Text processing. Sports analysts, scouts, training, and health staff frequently process textual data, such as scouting reports or injury and game reports, to identify talent or monitor athlete health and performance. These documents contain domain-specific terminology that is difficult for traditional automated systems to recognize accurately. Analysts or scouts may, furthermore, be looking for evidence of custom concepts, such as specific injury risks or recovery markers, or individual and team-specific performance indicators (e.g., regarding decision-making under pressure, tactical discipline, or spatial awareness). In medical and legal research, IML systems such as *abstrackr* [50] have successfully facilitated document screening tasks by allowing users to iteratively label documents and text fragments as relevant, enabling the system to reclassify publications and reduce user workload. Integrating similar workflows into sports practice could allow sports experts to build custom models for analyzing and processing their textual data, for example, to automatically highlight high-potential indicators in scouting reports, or analyze game and injury reports for precursors to non-contact injuries or cardiac defects.

Semantic segmentation. Sports analysts increasingly rely on image segmentation to identify specific game elements in image and video data, such as ball coordinates in table tennis or waterlines in canoeing [19]. Traditional pixel-level annotation for these tasks is laborious, yet automated systems may struggle with heterogeneous image input and required domain knowledge to correctly interpret the images [9]. IML systems such as *Crayons* have let users incrementally train classifiers by directly interacting with image regions (e.g., 'painting' the correct label onto them) [16]. Modern tools like *ilastik* utilize similar interactive workflows to refine object classification and tracking through user feedback [4]. These forms of interaction could enable analysts to rapidly adapt

computer vision models to specific venues, athletes, lighting conditions, or sports characteristics, enabling more precise tactical and performance analysis.

Activity recognition. Analyzing player behavior in sports that involve complex movements, such as hockey [6], requires precise tracking and labeling mechanisms to recognize meaningful actions, such as passing or shooting, from wearables or camera data [19]. These must work across many different athletes and conditions. However, standard models can fail to capture technical nuances or unique signatures in movement data, for example, related to temporary or persistent impairments [13]. In the music domain, IML systems like *Wekinator* [18] have enabled users to build custom gesture recognizers that process tracking data to control an instrument or steer music articulation. In biology, the IML system *JAABA* [28] has supported researchers in constructing custom datasets of researcher-defined individual and social behavior patterns in animals such as mice and larvae. These tools enable the interactive definition of relationships between real-time sensor inputs and custom-defined action outputs, such as gestures or social behavior patterns. They thus allow domain experts to build personalized models for specific techniques or individuals without requiring large-scale pre-labeled datasets. Similar approaches could be beneficial to sports experts, for example, to detect sport or team-specific tactical patterns (e.g., press, counter-attack in football) or individual training-relevant events in movement data (e.g., serve, return in tennis), or to retain a model's utility during a player's recovery and rehabilitation process.

5.2 Practical advice and challenges in applying and researching interactive machine learning

We have highlighted several opportunities where IML could support sports practice. But as of now, there may still be uncertainty about how SportsHCI research can adopt IML for their use cases and which barriers it may face. To facilitate the adoption of IML in SportsHCI research, we therefore briefly highlight existing tools and open challenges in developing IML systems.

A practical way to approach IML is to think of an IML system as realizing the four components *user*, *data*, *model*, and *interface* [12]. These components can further be separated into frontend and backend modules by applying intelligent user interface architectures [54]. Standard libraries like *scikit-learn* or *PyTorch* provide support to realize the modeling components of those architectures (e.g., to implement online learners). For their data and interface components, tools such as *MSP* [3] or *NOVA* [24] can be used to facilitate data processing, especially of multimodal and multi-sensor input. This is of particular importance to IML applications in sports, since sports data is commonly multimodal, for example, combining video and wearables data. This requires multimodal processing both on the frontend for effective user interactions and on the backend to handle training data. IML researchers can draw on guidance from multimodal interaction to handle the processing and representation challenges associated with these forms of data (e.g., [35]). Similarly, reviews on IML (e.g., [12]) provide design principles to create effective interfaces for user steering and data curation, and point to specific example systems for further details and inspiration.

While IML offers mature tooling and support for practical implementation, research on IML in sports can meaningfully contribute to addressing broader research challenges, for example, regarding the intersection of IML and deep learning. While AI models in sports heavily rely on deep learning to handle high-dimensional data, these models are often data-hungry and too opaque for standard interaction loops. Resolving the tension between interaction and deep learning remains, however, an active research endeavor [44]. New forms of IML will be required to bridge the gap between performant deep learning and the transparency and latency requirements of IML. Furthermore, sports involves highly specific team or individual concepts that need to be conveyed to the learner. Since this learner often remains a black box to the user, predictions can become intransparent, hindering the user's ability to steer the model [47]. Forms of explanatory IML [47] must be pursued that ensure interaction and explainability are placed on equal footing. Such systems will need to be measured by their ability to support practitioner steering, trust calibration, and fit with established workflows, as well as the interaction burden required to keep the system useful in practice. IML research in sports can meaningfully contribute to these broader research challenges by serving as a testbed for capturing and conveying expert concepts.

6 Limits and Emerging Directions

Across this article, we have argued that IML can address the disconnect between the AI and sports disciplines. However, IML may not always be the optimal, or at least not the only path forward. For example, IML could be critiqued for being too focused on technical details. From this perspective, something broader in scope, like Participatory Design [14], may be better suited to address underlying issues of misunderstanding and power dynamics for AI in sports. This critique points to an important limit, but it does not diminish the specific contribution of IML within a broader methodological space. Rather than treating it as a universal solution, IML is best understood as one among multiple approaches for integrating AI with sports practice. It demands a particular view on the design of ML systems—one where interaction and model training and structure stand on equal footing and are known to influence each other—that provides a very practical way to solve issues of data scarcity, concept drift, and customization in practice. As such, it does not deny or negate the utility of other approaches—not even a traditional ML approach if concepts and data are sufficiently well-defined. Instead, it facilitates approaches that focus on integration with practice. For example, within a Participatory Design loop, IML remains highly potent as a technical solution to address individual circumstances by giving people operational control over model inputs, structures, and outcomes. In this way, IML helps to translate Participatory Design principles like user empowerment into functional, technical terms that align with the language and conceptions of ML research to realize ML-based systems for sports practice.

It might also be argued that the rise of large language models (LLMs) raises a question for the relevance of IML, because many useful adaptations can now be achieved through prompts, examples,

and other forms of in-context learning rather than by updating or retraining a model. We admit that this is indeed a point of tension for the concept of IML as it is traditionally defined. Most definitions of IML have explicitly focused on the role of the user to direct model *training* (e.g., [12, 16, 33, 46]). One could, of course, argue that changing actual model weights, features, and structures has a more long-lasting and fundamental impact on ML models, including LLMs. After all, this is what contemporary LLM alignment techniques like RLHF [7] and DPO [37] strive to accomplish. But, in the age of LLMs, IML may indeed need an updated definition. For most use cases, there is no feasible way that users could affect the underlying structures or training of deep learning models that are a complete black box to them. To address this, we propose that IML may instead be defined more appropriately to be about persistently shaping model *behavior*, rather than model weights or structures. Under this definition, activities like in-context learning and interactive prompt engineering do, in fact, come into play. However, a single prompt or one-off correction is not sufficient. Users must be put in a position to meaningfully steer system behavior by interactively building up and iterating upon model updates over time. The success of such an IML approach should then be measured in part by the perceived degree of user control over ML outcomes, similarly to how a concept like direct manipulation is more appropriately measured by the perceived degree of control over system behavior than by the actual underlying functions [42]. Such a broader definition of IML will need to be discussed more thoroughly than there is space in this article. But we want to initiate and provoke this discussion now because we believe that such an approach could make the core principles of IML ever more relevant today.

7 Conclusion

In this article, we have argued that the central problem of AI in sports is practitioner participation in model development and control over model behavior in use. While sports technology produces vast amounts of data, the rigid nature of traditional ML pipelines often fails to turn this data into useful tools because sports practitioners remain largely limited to consuming model outputs. Human-in-the-loop systems improve on this by involving practitioners more directly, but still commonly restrict them to narrow roles defined in advance by the designers of the system. IML offers a solution to this. It allows practitioners to inspect, contest, and steer model behavior in relation to their own concepts, cases, and performance criteria in use. It thus allows them to customize and tailor these systems to their individual and unique requirements and needs. This does not mean that all sports AI should become IML, nor that IML is the only path forward. Instead, it demonstrates that practitioner steering and integration with sporting practice should be treated as core requirements when designing AI for sport. We posit that IML is one particularly strong way to pursue this goal because it makes interaction a key part of how model behavior is formed, revised, and kept useful over time. We therefore call upon the SportsHCI community to thoroughly examine IML for AI in sports and to realize our vision of AI technology that truly facilitates sports practice.

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References

[1] Shaojun Ai, Jiaming Na, Varuna De Silva, and Michael Caine. 2021. A Novel Methodology for Automating Spatio-Temporal Data Classification in Basketball Using Active Learning. In *2021 IEEE 2nd International Conference on Pattern Recognition and Machine Learning (PRML)*, Adams W. K. Kong, Vijayakumar Varadarajan, Keren Fu, and Dakun Lai (Eds.). 39–45. doi:10.1109/PRML52754.2021.9520715

[2] Saleema Amershi, Maya Cakmak, William Bradley Knox, and Todd Kulesza. 2014. Power to the People: The Role of Humans in Interactive Machine Learning. *AI Magazine* 35, 4 (Dec. 2014), 105–120. doi:10.1609/aimag.v35i4.2513

[3] Michael Barz, Omair Shahzad Bhatti, Bengt Lüers, Alexander Prange, and Daniel Sonntag. 2021. Multisensor-Pipeline: A Lightweight, Flexible, and Extensible Framework for Building Multimodal-Multisensor Interfaces. In *Companion Publication of the 2021 International Conference on Multimodal Interaction*, Sharon Oviatt, Albert Ali Salah, and Guoying Zhao (Eds.). ACM, Montreal QC Canada, 13–18. doi:10.1145/3461615.3485432

[4] Stuart Berg, Dominik Kutra, Thorben Kroeger, Christoph N. Straehle, Bernhard X. Kausler, Carsten Haubold, Martin Schiegg, Janez Ales, Thorsten Beier, Markus Rudy, Kemal Eren, Jaime I. Cervantes, Buote Xu, Fynn Beuttenmueller, Adrian Wolny, Chong Zhang, Ullrich Koethe, Fred A. Hamprecht, and Anna Kreshuk. 2019. ilastik: interactive machine learning for (bio)image analysis. *Nature Methods* 16, 12 (Dec. 2019), 1226–1232. doi:10.1038/s41592-019-0582-9 Publisher: Nature Publishing Group.

[5] Martin Buchheit. 2014. Monitoring training status with HR measures: do all roads lead to Rome? *Frontiers in Physiology* 5 (Feb. 2014). doi:10.3389/fphys.2014.00073

[6] Zixi Cai, Helmut Neher, Kanav Vats, David A. Clausi, and John Zelek. 2019. Temporal Hockey Action Recognition via Pose and Optical Flows, Ali Farhadi, David Crandall, Imari Sato, Jianxin Wu, Robert Pless, and Zeynep Akata (Eds.). 0–0. https://openaccess.thecvf.com/content_CVPRW_2019/html/CVSports/Cai_Temporal_Hockey_Action_Recognition_via_Pose_and_Optical_Flows_CVPRW_2019_paper.html

[7] Paul F. Christiano, Jan Leike, Tom B. Brown, Miljan Martic, Shane Legg, and Dario Amodei. 2017. Deep reinforcement learning from human preferences. In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17)*. Curran Associates Inc., Red Hook, NY, USA, 4302–4310.

[8] João Gustavo Claudino, Daniel de Oliveira Capanema, Thiago Vieira de Souza, Julio Cerca Serrão, Adriano C. Machado Pereira, and George P. Nassis. 2019. Current Approaches to the Use of Artificial Intelligence for Injury Risk Assessment and Performance Prediction in Team Sports: a Systematic Review. *Sports Medicine - Open* 5, 1 (July 2019), 28. doi:10.1186/s40798-019-0202-3

[9] Dazhen Deng, Jiang Wu, Jiachen Wang, Yihong Wu, Xiao Xie, Zheng Zhou, Hui Zhang, Xiaolong (Luke) Zhang, and Yingcai Wu. 2021. EventAnchor: Reducing Human Interactions in Event Annotation of Racket Sports Videos. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*, Katherine Isbister and Takeo Igarashi (Eds.). Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3411764.3445431

[10] Nathan DeVrio, Vimal Mollyn, and Chris Harrison. 2023. SmartPoser: Arm Pose Estimation with a Smartphone and Smartwatch Using UWB and IMU Data. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. Association for Computing Machinery, New York, NY, USA, 1–11. doi:10.1145/3586183.3606821

[11] Ye Ding, Myunghee Kim, Scott Kuindersma, and Conor J. Walsh. 2018. Human-in-the-loop optimization of hip assistance with a soft exosuit during walking. *Science Robotics* 3, 15 (Feb. 2018), eaar5438. doi:10.1126/scirobotics.aar5438 Publisher: American Association for the Advancement of Science.

[12] John J. Dudley and Per Ola Kristensson. 2018. A Review of User Interface Design for Interactive Machine Learning. *ACM Trans. Interact. Intell. Syst.* 8, 2 (June 2018), 8:1–8:37. doi:10.1145/3185517

[13] Jared Duval, Laia Turmo Vidal, Elena Márquez Segura, Yinchu Li, and Annika Waern. 2023. Reimagining Machine Learning's Role in Assistive Technology by Co-Designing Exergames with Children Using a Participatory Machine Learning Design Probe. In *The 25th International ACM SIGACCESS Conference on Computers*

[1] https://cst.dfki.de/

and Accessibility, Erin Brady and Maria Wolters (Eds.). ACM, New York NY USA, 1–16. doi:10.1145/3597638.3608421

[14] Niklas Elmqvist, Eve Hoggan, Hans-Jörg Schulz, Marianne Graves Petersen, Peter Dalsgaard, Ira Assent, Olav W. Bertelsen, Akhil Arora, Kaj Grønbæk, Susanne Bødker, Clemens Nylandsted Klokmose, Rachel Charlotte Smith, Sebastian Hubenschmid, Christoph A. Johns, Gabriela Molina León, Anton Wolter, Johannes Ellemose, Vaishali Dhanoa, Simon Aagaard Enni, Mille Skovhus Lunding, Karl-Emil Kjær Bilstrup, Juan Sánchez Esquivel, Luke Connelly, Rafael Pablos Sarabia, Morten Birk, Joachim Nyborg, Stefanie Zollmann, Tobias Langlotz, Meredith Siang-Yun Chou, Jens Emil Sloth Grønbæk, Michael Wessely, Yijing Jiang, Caroline Berger, Duosi Dai, Michael Mose Biskjaer, Germán Leiva, Jonas Frich, Eva Eriksson, Kim Halskov, Thorbjørn Mikkelsen, Nearchos Potamitis, Michel Yildirim, Arvind Srinivasan, Jeanette Falk, Nanna Inie, Ole Sejer Iversen, and Hugo Andersson. 2025. Participatory AI: A Scandinavian Approach to Human-Centered AI. doi:10.48550/arXiv.2509.12752 arXiv:2509.12752 [cs].

[15] Don Samitha Elvitigala, Armağan Karahanoğlu, Andrii Matviienko, Laia Turmo Vidal, Dees Postma, Michael D Jones, Maria F. Montoya, Daniel Harrison, Lars Elbæk, Florian Daiber, Lisa Anneke Burr, Rakesh Patibanda, Paolo Buono, Perttu Hämäläinen, Robby Van Delden, Regina Bernhaupt, Xipei Ren, Vincent Van Rheden, Fabio Zambetta, Elise Van Den Hoven, Carine Lallemand, Dennis Reidsma, and Florian 'Floyd' Mueller. 2024. Grand Challenges in SportsHCI. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, 1–20. doi:10.1145/3613904.3642050

[16] Jerry Alan Fails and Dan R. Olsen. 2003. Interactive machine learning. In *Proceedings of the 8th international conference on Intelligent user interfaces (IUI '03)*, David Leake, Lewis Johnson, and Elisabeth Andre (Eds.). Association for Computing Machinery, New York, NY, USA, 39–45. doi:10.1145/604045.604056

[17] Javier Fernández, F C Barcelona, Luke Bornn, and Dan Cervone. 2019. Decomposing the Immeasurable Sport: A deep learning expected possession value framework for soccer. In *Proceedings of the 13th annual MIT SLOAN sports analytics conference*, Daryl Morey and Jessica Gelman (Eds.). Boston, MA, USA.

[18] Rebecca Anne Fiebrink. 2011. *Real-time Human Interaction with Supervised Learning Algorithms for Music Composition and Performance*. PhD Thesis. Princeton University, Princeton, NJ, USA.

[19] Indrajeet Ghosh, Sreenivasan Ramasamy Ramamurthy, Avijoy Chakma, and Nirmalya Roy. 2023. Sports analytics review: Artificial intelligence applications, emerging technologies, and algorithmic perspective. *WIREs Data Mining and Knowledge Discovery* 13, 5 (2023), e1496. doi:10.1002/widm.1496 _eprint: https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/widm.1496.

[20] Marco Gillies. 2019. Understanding the Role of Interactive Machine Learning in Movement Interaction Design. *ACM Trans. Comput.-Hum. Interact.* 26, 1 (Feb. 2019), 5:1–5:34. doi:10.1145/3287307

[21] Lijie Guo, Elizabeth M. Daly, Oznur Alkan, Massimiliano Mattetti, Owen Cornec, and Bart Knijnenburg. 2022. Building Trust in Interactive Machine Learning via User Contributed Interpretable Rules. In *Proceedings of the 27th International Conference on Intelligent User Interfaces (IUI '22)*, Simone Stumpf, Tuukka Ruotsalo, and Krzysztof Gajos (Eds.). Association for Computing Machinery, New York, NY, USA, 537–548. doi:10.1145/3490099.3511111

[22] Robert S. Gutzwiller and John Reeder. 2017. Human interactive machine learning for trust in teams of autonomous robots. In *2017 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, Mica Endsley, Christian Lebiere, and Tom Ziemke (Eds.). 1–3. doi:10.1109/COGSIMA.2017.7929607 ISSN: 2379-1675.

[23] Fabian Hammes, Alexander Hagg, Alexander Asteroth, and Daniel Link. 2022. Artificial Intelligence in Elite Sports—A Narrative Review of Success Stories and Challenges. *Frontiers in Sports and Active Living* 4 (July 2022). doi:10.3389/fspor.2022.861466 Publisher: Frontiers.

[24] Alexander Heimerl, Tobias Baur, Florian Lingenfelser, Johannes Wagner, and Elisabeth André. 2019. NOVA - A tool for eXplainable Cooperative Machine Learning. In *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*, Nadia Bianchi-Berthouze, Julien Epps, Andrea Kleinsmith, and Rosalind Picard (Eds.). 109–115. doi:10.1109/ACII.2019.8925519 ISSN: 2156-8111.

[25] Mat Herold, Floris Goes, Stephan Nopp, Pascal Bauer, Chris Thompson, and Tim Meyer. 2019. Machine learning in men's professional football: Current applications and future directions for improving attacking play. *International Journal of Sports Science & Coaching* 14, 6 (Dec. 2019), 798–817. doi:10.1177/1747954119879350 Publisher: SAGE Publications.

[26] Tomislav Horvat and Josip Job. 2020. The use of machine learning in sport outcome prediction: A review. *WIREs Data Mining and Knowledge Discovery* 10, 5 (2020), e1380. doi:10.1002/widm.1380 _eprint: https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/widm.1380.

[27] Anthony David Jameson, Aaron Spaulding, and Neil Yorke-Smith. 2009. Introduction to the Special Issue on "Usable AI". *AI Magazine* 30, 4 (Sept. 2009), 11–11. doi:10.1609/aimag.v30i4.2273

[28] Mayank Kabra, Alice A. Robie, Marta Rivera-Alba, Steven Branson, and Kristin Branson. 2013. JAABA: interactive machine learning for automatic annotation of animal behavior. *Nature Methods* 10, 1 (Jan. 2013), 64–67. doi:10.1038/nmeth.2281 Publisher: Nature Publishing Group.

[29] Hoang M Le, Peter Carr, Yisong Yue, and Patrick Lucey. 2017. Data-driven ghosting using deep imitation learning. In *Proceedings of the 11th annual MIT SLOAN sports analytics conference*, Daryl Morey and Jessica Gelman (Eds.). Boston, MA, USA.

[30] John D. Lee and Katrina A. See. 2004. Trust in Automation: Designing for Appropriate Reliance. *Human Factors* 46, 1 (March 2004), 50–80. doi:10.1518/hfes.46.1.50_30392 Publisher: SAGE Publications Inc.

[31] Arash Mahyari, Peter Pirolli, and Jacqueline A. LeBlanc. 2022. Real-Time Learning from an Expert in Deep Recommendation Systems with Application to mHealth for Physical Exercises. *IEEE Journal of Biomedical and Health Informatics* 26, 8 (Aug. 2022), 4281–4290. doi:10.1109/JBHI.2022.3167314

[32] Riccardo Miotto, Li Li, Brian A. Kidd, and Joel T. Dudley. 2016. Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records. *Scientific Reports* 6, 1 (May 2016), 26094. doi:10.1038/srep26094

[33] Eduardo Mosqueira-Rey, Elena Hernández-Pereira, David Alonso-Ríos, José Bobes-Bascarán, and Angel Fernández-Leal. 2023. Human-in-the-loop machine learning: a state of the art. *Artificial Intelligence Review* 56, 4 (April 2023), 3005–3054. doi:10.1007/s10462-022-10246-w

[34] Heleen Muijlwijk, Martijn C. Willemsen, Barry Smyth, and Wijnand A. IJsselsteijn. 2024. Benefits of Human-AI Interaction for Expert Users Interacting with Prediction Models: a Study on Marathon Running. In *Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24)*, Bart Knijnenburg, Osnat Mokryn, Dorota Glowacka, Dennis Para, and Ofra Amir (Eds.). Association for Computing Machinery, New York, NY, USA, 245–258. doi:10.1145/3640543.3645205

[35] Sharon Oviatt, Björn Schuller, Philip R. Cohen, Daniel Sonntag, Gerasimos Potamianos, and Antonio Krüger (Eds.). 2018. *The Handbook of Multimodal-Multisensor Interfaces: Signal Processing, Architectures, and Detection of Emotion and Cognition - Volume 2*. Vol. 21. Association for Computing Machinery and Morgan & Claypool.

[36] N. Owens, C. Harris, and C. Stennett. 2003. Hawk-eye tennis system. In *2003 International Conference on Visual Information Engineering VIE 2003*, Paola Hobson and John Illingworth (Eds.). 182–185. doi:10.1049/cp:20030517 ISSN: 0537-9989.

[37] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D. Manning, Stefano Ermon, and Chelsea Finn. 2023. Direct Preference Optimization: Your Language Model is Secretly a Reward Model. *Advances in Neural Information Processing Systems* 36 (Dec. 2023), 53728–53741. https://proceedings.neurips.cc/paper_files/paper/2023/hash/a85b405ed65c6477a4fe8302b5e06ce7-Abstract-Conference.html

[38] Robert Rein and Daniel Memmert. 2016. Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus* 5, 1 (Aug. 2016), 1410. doi:10.1186/s40064-016-3108-2

[39] Chris Richter, Martin O'Reilly, and Eamonn Delahunt. 2024. Machine learning in sports science: challenges and opportunities. *Sports Biomechanics* 23, 8 (Aug. 2024), 961–967. doi:10.1080/14763141.2021.1910334 Publisher: Routledge _eprint: https://doi.org/10.1080/14763141.2021.1910334.

[40] Thomas Seidl, Aditya Cherukumudi, Andrew Hartnett, Peter Carr, and Patrick Lucey. 2018. Bhostgusters: Realtime Interactive Play Sketching with Synthesized NBA Defenses. In *Proceedings of the 12th annual MIT SLOAN sports analytics conference*, Daryl Morey and Jessica Gelman (Eds.). Boston, MA, USA.

[41] Dhruv R. Seshadri, Ryan T. Li, James E. Voos, James R. Rowbottom, Celeste M. Alfes, Christian A. Zorman, and Colin K. Drummond. 2019. Wearable sensors for monitoring the physiological and biochemical profile of the athlete. *npj Digital Medicine* 2, 1 (July 2019), 72. doi:10.1038/s41746-019-0150-9

[42] Ben Shneiderman and Pattie Maes. 1997. Direct manipulation vs. interface agents. *Interactions* 4, 6 (Nov. 1997), 42–61. doi:10.1145/267505.267514

[43] Barry Smyth and Pádraig Cunningham. 2017. Running with Cases: A CBR Approach to Running Your Best Marathon. In *Case-Based Reasoning Research and Development (Lecture Notes in Computer Science, Vol. 10339)*, David W. Aha and Jean Lieber (Eds.). Springer International Publishing, Cham, 360–374.

[44] Daniel Sonntag, Michael Barz, and Thiago Gouvea. 2024. *A look under the hood of the Interactive Deep Learning Enterprise (No-IDLE)*. Technical Report. German Research Center for AI.

[45] Billy Sperlich, Peter Düking, Robert Leppich, and Hans-Christer Holmberg. 2023. Strengths, weaknesses, opportunities, and threats associated with the application of artificial intelligence in connection with sport research, coaching, and optimization of athletic performance: a brief SWOT analysis. *Frontiers in Sports and Active Living* 5 (Oct. 2023). doi:10.3389/fspor.2023.1258562 Publisher: Frontiers.

[46] Agnes Tegen, Paul Davidsson, and Jan A. Persson. 2021. A Taxonomy of Interactive Online Machine Learning Strategies. In *Machine Learning and Knowledge Discovery in Databases*, Frank Hutter, Kristian Kersting, Jefrey Lijffijt, and Isabel Valera (Eds.). Springer International Publishing, Cham, 137–153. doi:10.1007/978-3-030-67661-2_9

[47] Stefano Teso and Kristian Kersting. 2019. Explanatory Interactive Machine Learning. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (AIES '19)*, Vincent Conitzer, Gillian Hadfield, and Shannon Vallor (Eds.). Association for Computing Machinery, New York, NY, USA, 239–245. doi:10.1145/3306618.3314293

[48] Laia Turmo Vidal, Annika Waern, Rosa Cabanas-Valdés, Lauren van Loo, Yinchu Li, and Karthik Venkataraman Meenaakshisundaram. 2025. Towards Personalized Physiotherapy through Interactive Machine Learning: A Conceptual Infrastructure Design for In-Clinic and Out-of-Clinic Support. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*, Naomi Yamashita, Vanessa Evers, Koji Yatani, Xianghua Ding, Bongshin Lee, Marshini Chetty, and Phoebe Toups-Dugas (Eds.). Association for Computing Machinery, New York, NY, USA, 1–19. doi:10.1145/3706598.3713823

[49] Eduardo Velloso, Andreas Bulling, and Hans Gellersen. 2013. MotionMA: motion modelling and analysis by demonstration. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. Association for Computing Machinery, New York, NY, USA, 1309–1318. doi:10.1145/2470654.2466171

[50] Byron C. Wallace, Kevin Small, Carla E. Brodley, Joseph Lau, and Thomas A. Trikalinos. 2012. Deploying an interactive machine learning system in an evidence-based practice center: abstrackr. In *Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium (IHI '12)*, Christopher C. Yang (Ed.). Association for Computing Machinery, New York, NY, USA, 819–824. doi:10.1145/2110363.2110464

[51] Hanchen Wang, Tianfan Fu, Yuanqi Du, Wenhao Gao, Kexin Huang, Ziming Liu, Payal Chandak, Shengchao Liu, Peter Van Katwyk, Andreea Deac, Anima Anandkumar, Karianne Bergen, Carla P. Gomes, Shirley Ho, Pushmeet Kohli, Joan Lasenby, Jure Leskovec, Tie-Yan Liu, Arjun Manrai, Debora Marks, Bharath Ramsundar, Le Song, Jimeng Sun, Jian Tang, Petar Veličković, Max Welling, Linfeng Zhang, Connor W. Coley, Yoshua Bengio, and Marinka Zitnik. 2023. Scientific discovery in the age of artificial intelligence. *Nature* 620, 7972 (Aug. 2023), 47–60. doi:10.1038/s41586-023-06221-2

[52] Zhe Wang, Petar Veličković, Daniel Hennes, Nenad Tomašev, Laurel Prince, Michael Kaisers, Yoram Bachrach, Romuald Elie, Li Kevin Wenliang, Federico Piccinini, William Spearman, Ian Graham, Jerome Connor, Yi Yang, Adrià Recasens, Mina Khan, Nathalie Beauguerlange, Pablo Sprechmann, Pol Moreno, Nicolas Heess, Michael Bowling, Demis Hassabis, and Karl Tuyls. 2024. TacticAI: an AI assistant for football tactics. *Nature Communications* 15, 1 (March 2024), 1906. doi:10.1038/s41467-024-45965-x

[53] Yang Yang and Yuanji Zhao. 2025. Personalized Sports Health Recommendation System Assisted by Q-Learning Algorithm. *International Journal of Human–Computer Interaction* 41, 4 (Feb. 2025), 1889–1901. doi:10.1080/10447318.2023.2295693 Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10447318.2023.2295693.

[54] Jan Zacharias, Michael Barz, and Daniel Sonntag. 2018. A Survey on Deep Learning Toolkits and Libraries for Intelligent User Interfaces. doi:10.48550/arXiv.1803.04818 arXiv:1803.04818 [cs].

[55] Abigail Zimmermann-Niefield, R. Benjamin Shapiro, and Shaun Kane. 2019. Sports and machine learning: How young people can use data from their own bodies to learn about machine learning. *XRDS* 25, 4 (July 2019), 44–49. doi:10.1145/3331071

[56] Abigail Zimmermann-Niefield, Makenna Turner, Bridget Murphy, Shaun K. Kane, and R. Benjamin Shapiro. 2019. Youth Learning Machine Learning through Building Models of Athletic Moves. In *Proceedings of the 18th ACM International Conference on Interaction Design and Children (IDC '19)*, Jerry A. Fails (Ed.). Association for Computing Machinery, New York, NY, USA, 121–132. doi:10.1145/3311927.3323139