Optimising the Use of Machine Learning and Computer Vision in Sport: An Ecological Dynamics Perspective.

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Optimizing the Use of Machine Learning and Computer Vision in Sport: An Ecological Dynamics Perspective

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Abstract

Although machine learning and computer vision is a growing area of research in sports analysis, its implementation in athlete development programs does not guarantee performance improvements. Developers typically design and implement machine learning and computer vision technologies into athlete development programs because of the high level of technical information on performance that can emerge. The value gained from this approach can be limited by siloed working practices in sports organizations and by sporadic approaches to athlete development which can negatively affect skill development. Here, we discuss why the design and integration of machine learning and computer vision in athlete development programs needs to be rationalized by a theoretical framework to guide effective collaborations between sport scientists, technologists, and practitioners. This position paper illustrates how the use (i.e., design and implementation) of machine learning and computer vision technologies in athlete development programs could be underpinned by the structural organization of a Department of Methodology (DoM), and that underpinned by a theoretical framework, such as ecological dynamics. We outline how the integration of machine learning and computer vision technology, underpinned by an ecological theoretical approach, can accomplish the following: (1) support representative learning design, (2) individualize training and assessment of athletes, and (3), enhance, but not replace, the quality of coaching within athlete development programs.

Keywords

ecological dynamics, Department of Methodology, machine learning, computer vision, sport science

Introduction

In recent years, the integration of technology into sports performance and analysis has significantly advanced, particularly with the emergence of methodologies such as machine learning and computer vision technologies, aimed at enriching athlete development programs and enhancing the work of professional support practitioners. Machine learning (ML) involves designing software capable of learning and making predictions or decisions, from large sets of performance data, while continually improving their accuracy by introducing more training data, simulating how humans learn from additional sources of information (Kufel et al., 2023). Computer Vision (CV) extracts and categorizes information embedded within images and videos, allowing computers to gather information from the real world, just as the eye allows humans to perceive and gather information around us (Voulodimos et al., 2018). These technologies could improve athlete development and performance preparation in sport by reducing practitioner workload, allowing athletes to remain within their training environment for performance analysis, supporting practitioners to deliver more individualized and contextualized development and performance preparation experiences, by enriching the quality of feedback provision (Brefeld et al., 2021). However, implementing these technologies in athlete development programs requires a high level of specialized sport science knowledge, so developers typically carry out its application without multidisciplinary support staff, which in sports organizations may result in "siloed" working (Araújo et al., 2020). Siloed working occurs when practitioners from different disciplines (e.g., coaches, performance analysts, strength and conditions trainers, physiotherapists, biomechanics, and nutritionists) work in isolation from one another, which may lead to sporadic and reductive approaches to athlete development and preparation and ineffective practice environments (Otte et al., 2020). Therefore, to avoid siloed working in a sports organization, it is crucial to design an organizational structure that supports the integration of knowledge and skills of sports scientists, support staff, and practitioners (Rothwell et al., 2020).

A theoretical framework (a conceptual platform, grounded in ideas and principles, for guiding collective contributions of and connections between professional practitioners) could help rationalize implementation of ML and CV technologies within athlete development and preparation, perhaps mitigating siloed working within multidisciplinary support teams. However, there has been no attempt to discuss how a theoretical framework could enrich athlete development programs by supporting the integration of ML and CV technologies and how this could enhance the performance of athletes and practitioners (Herold et al., 2019; Yu et al., 2021).

Typically, sports science, medical, and technological support in high-performance sports occurs in a highly structured, isolated model indicative of siloed working (Otte et al., 2020). In this model, athletes are "passed" from department to department focusing on different performance dimensions (e.g., physical conditioning, tactical analysis, psychological preparation, health preparation), and then the athletes are "worked on" by subdiscipline specialists. This siloed approach in sports organization is exemplified in a model from elite football (Deconche et al., 2019). While the athlete is placed at the center of the performance preparation and development process, the different departments have limited inter-departmental collaborations and correspondence, which may risk a lack of cohesion in athlete development as the goals of one department may not be shared with another (Figure 1, next page). Therefore, when additional practitioners (i.e., developers) are included in this working model to enrich the athlete development process with ML and CV, it could exacerbate siloed working practices and reduce effectiveness of athlete development and preparation.

A collaborative approach to integrating ML and CV technologies for athlete learning and development in sports could be achieved through implementing an organizational structure termed a "Department of Methodology" (DoM) (Rothwell et al., 2020). The DoM aims to improve the multi-disciplinary approach to athlete development programs by facilitating correspondence, collaboration and sharing of expert knowledge, skills, ideas, and technologies between professional practitioners under the rubric of ecological dynamics. Ecological dynamics in sports integrates principles from ecological psychology and refers to the interaction between athletes, the environment, and the task. It explains how athletes act, perceive, and adapt during training or competition (Araújo et al., 2006). Therefore, an organizational structure conceived around a DoM can support the following: (1) design of information-rich practice environments (i.e., including relevant sources such as acoustic, haptic, proprioceptive, visual, and augmented information as feedback), (2) communication of coherent ideas, and (3), shared principles and conceptual language that guide the emergence of multi-dimensional behaviors in athlete performance (Rothwell et al., 2020). For example, in practice, an athlete development program conceived under a DoM is (1) individual-centered, (2) highly supportive of subdisciplines within a large multi-disciplinary team working in unison to achieve a common goal, (3) advocates for the "co-design" of training sessions through the sharing of information, skills, technologies and ideas, and (4), provides a voice for athletes to self-regulate their performance preparation and development. See Figure 2, next page, which is based on a framework proposed by Otte et al. (2022).

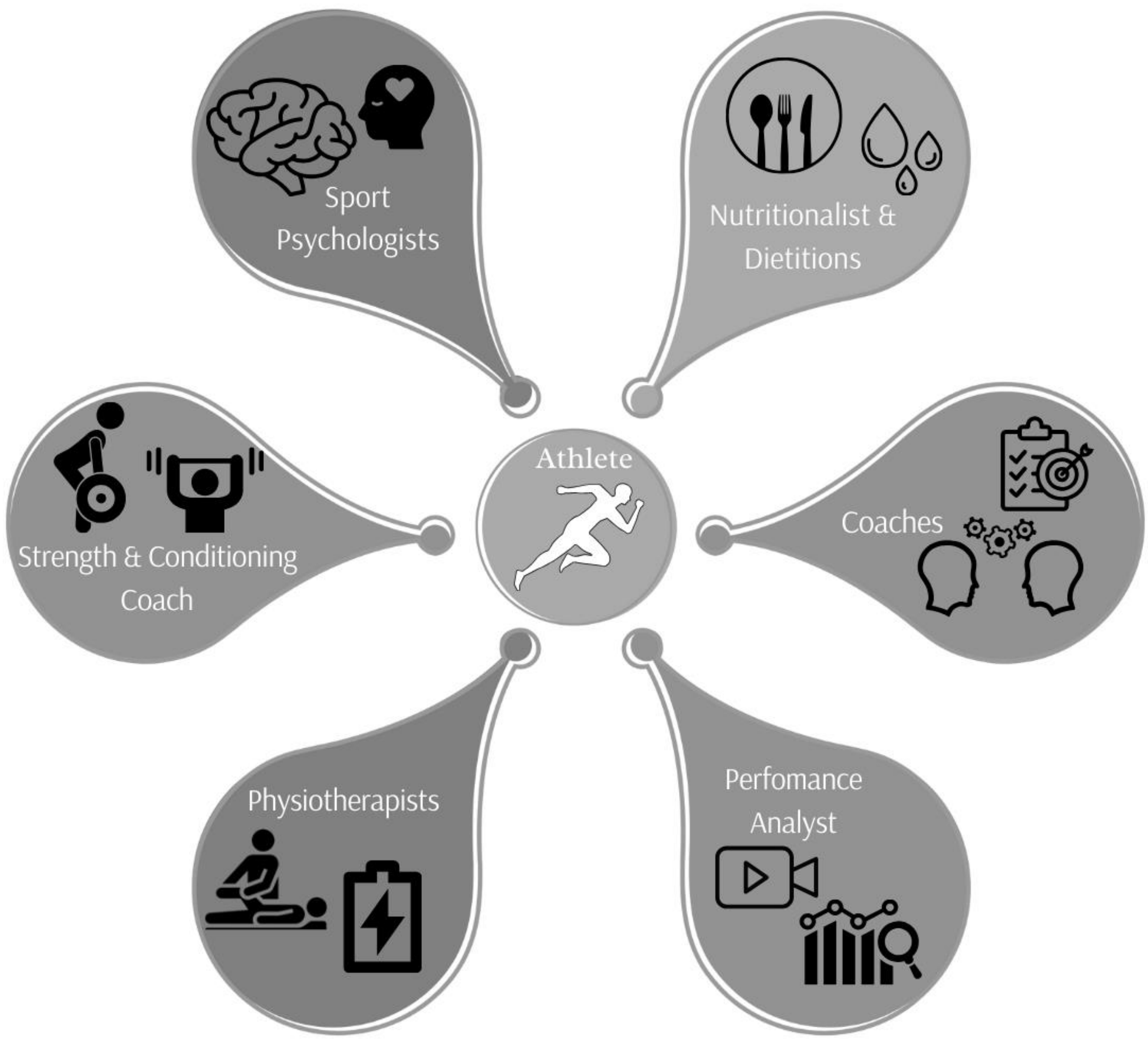

Figure 1. Demonstration of the current approach to multidisciplinary teams within athlete development programs (adapted from Deconche et al., 2019).

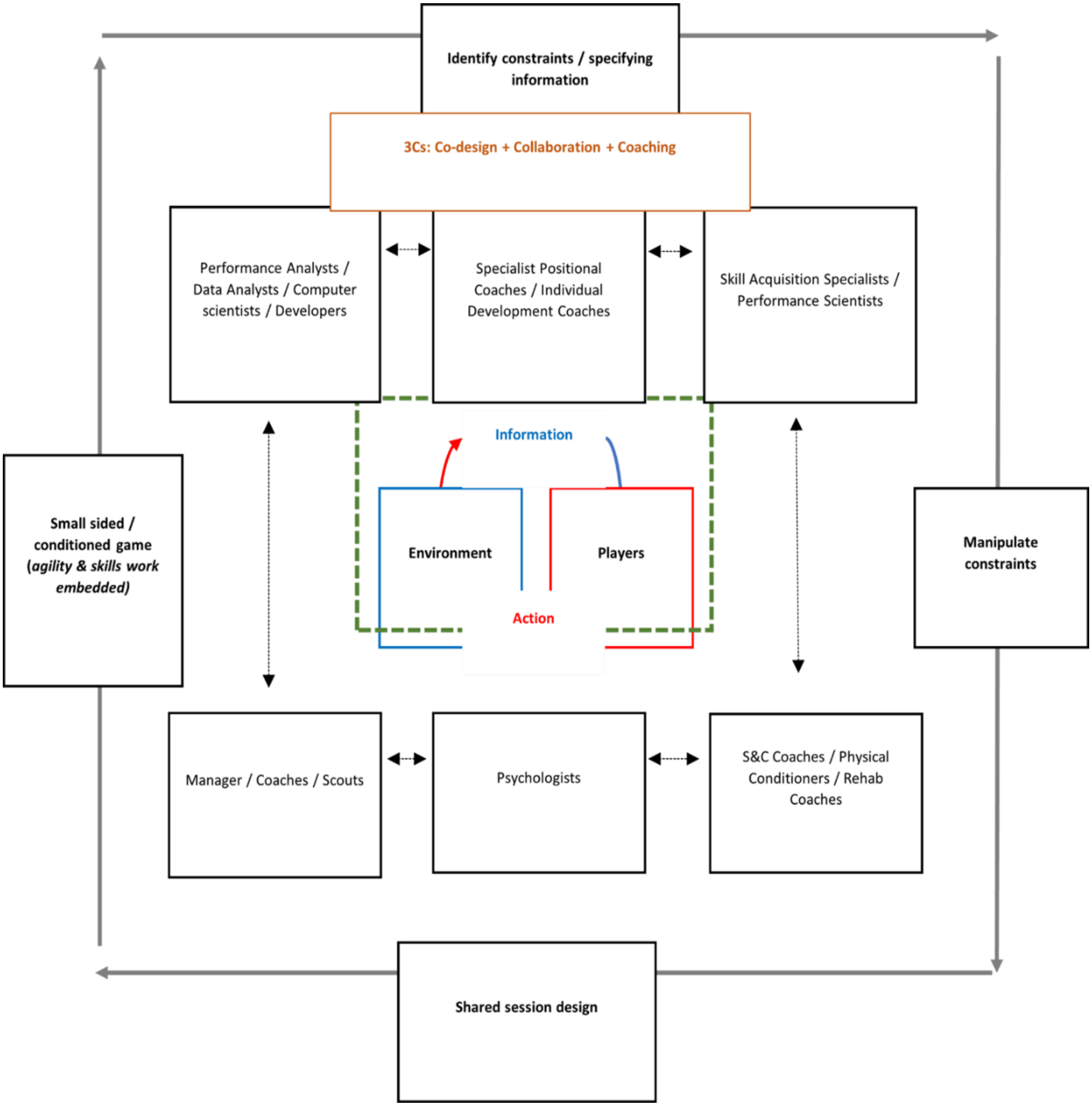

Figure 2. Outline of a practical example of how training sessions could be collaboratively developed and enriched under the framework of a DoM.

Since the unsupported implementation of ML and CV is not guaranteed to improve player performance (Herold et al., 2019), theoretical underpinning is a much-needed advance because of increasing applications of ML and CV technologies to improve sports performance. Stone et al. (2018) outlined how ecological dynamics could enhance the applications of new technologies within athlete development programs to improve athlete performance. While Stone et al. (2018) raised an important issue, they did not discuss principles that could support the collaboration of practitioners during the application of new technologies within athlete development programs. In sum, a DoM can support the integration of domain experts to provide different insights that enrich athlete development and performance preparation with ML and CV technologies. In this position paper, we argue how and why a DoM supported by ecological dynamics may optimize the application of ML and CV technologies for athlete learning and development in sports by providing a framework that supports the collaboration of practitioners and the design of effective training environments.

Enhancing Learning Design by Harnessing Machine Learning and Computer Vision: Under an Ecological Framework

Talent development is considered a dynamic process as learners interact continuously with their environment. This invites the emergence of movement solutions that can respond to changing demands on learners and changing environmental constraints (e.g., the involvement of other athletes, weather conditions, crowds of spectators, and variation in learning tasks) highlighting the need for representative learning environments (Pinder et al., 2011; Seifert et al., 2019). A representative learning environment is designed with constraints that reflect a specific performance environment (i.e., the practice environment is more natural and is comparable to a performance context) (Pinder et al., 2011). Under a DoM, coaches are the designers of practice environments, but they need support from other experts (see Figure 2) to enhance the representativeness of practice environments to support athletes (Hadiana et al., 2020; Nelson et al., 2014).

Analysis of an athlete's performance provides practitioners with understanding of the athlete's developmental needs. Traditional methods of analyzing movement, such as 3D marker-based motion capture, require markers be placed on athletes while they perform, but this method is expensive, intrusive, and time-consuming (van der Kruk & Reijne, 2018). This approach focuses on the micro-movements of athletes and typically must be used inside a laboratory which is not a representative performance environment and thus affects movement patterns and interferes with athlete development (Neumann et al., 2018; Pinder et al., 2011). Human Pose Estimation (HPE) is an approach integrating ML and CV for detecting and tracking joints and limbs with images and videos without the need for additional markers. This allows practitioners to perform unrestricted movement analysis in an athlete's natural training environment, avoiding unnecessary alterations of performance-based interactions between the athlete, task, and environment (Giblin et al., 2016; Pinder et al., 2011). HPE currently cannot provide 100% accuracy but is continuously improving. When combined with the domain expertise of coaches, HPE could provide practitioners with a better understanding of performance in a natural training environment thus allowing them to make informed decisions about athlete development and performance preparation (Badiola-Bengoa & Mendez-Zorrilla, 2021).

To facilitate this process, sports organizations could operate within a framework that includes practitioner collaboration and training environment design principles. The ecological framework (see Figure 3, next page) incorporates a DoM, which enables knowledge exchange between practitioners through a common conceptual language and practice design principles derived from ecological dynamics (Rothwell et al., 2020). It is also important to allow practitioners to manipulate the training environment to guide the behavior of athletes. The constraints-led approach advocates a less prescriptive approach to coaching, allowing the training environment to illicit intrinsic feedback in athletes to improve development, a crucial pillar of the ecological framework (see Figure 3) (Renshaw et al., 2019). For example, a football team operating under a DoM could involve coaches who, using their domain knowledge and key principles from ecological dynamics (i.e., representative learning design and constraints led approach), want to improve the team's ability to pass through the defensive line. A small-sided game is implemented where attackers get rewarded for passing the ball through the opposition's defensive line. Performance analysts may use the performance data from developer-implemented HPE to discover strengths and weaknesses during and after the activity, thus allowing the coach to make more informed modifications for the next session.

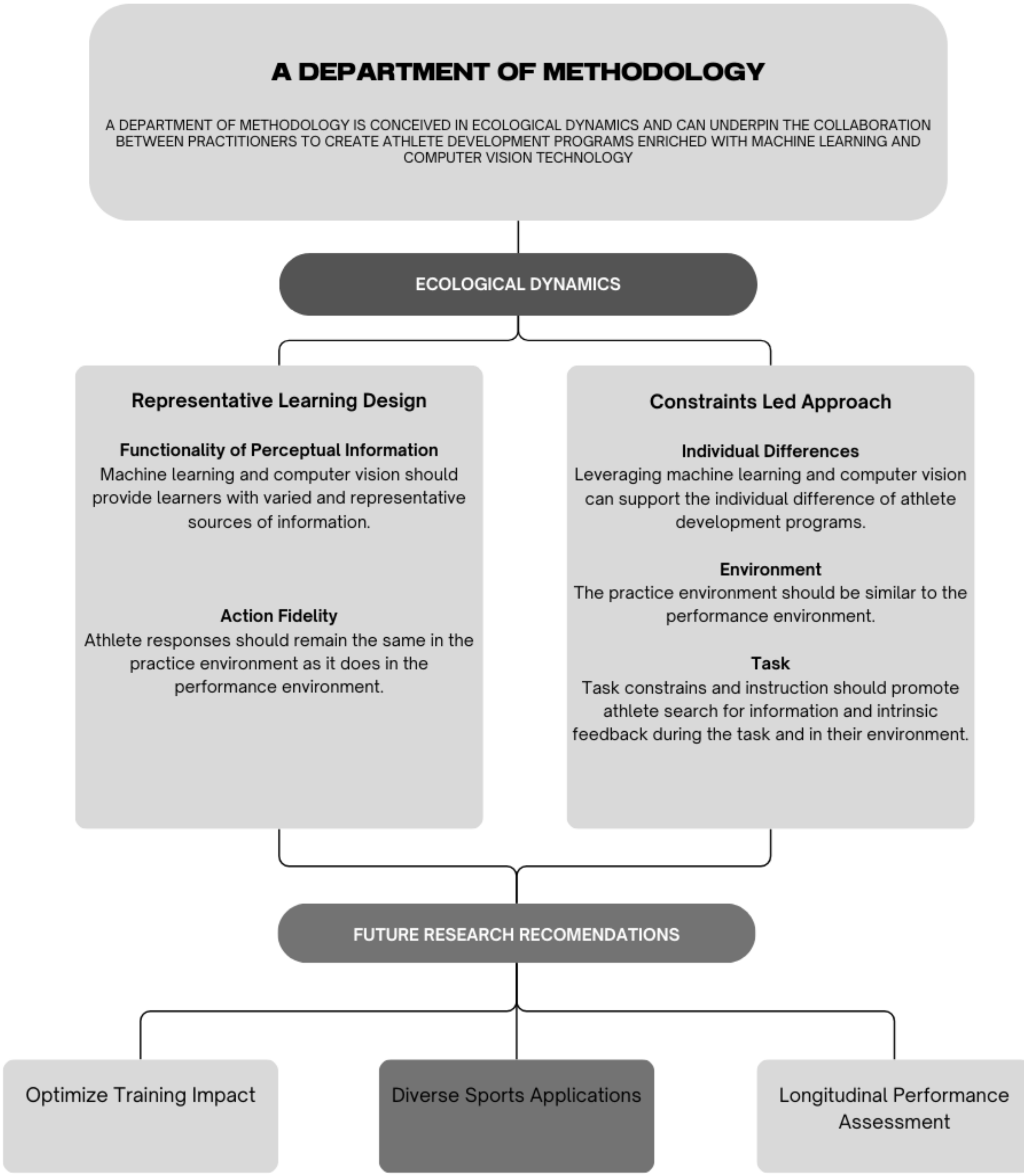

Figure 3. Department of Methodology and ecological dynamics: A pillared framework to optimize the design and implementation of machine learning and computer vision technology in sport.

Optimizing Individualized Training Approaches Using Machine Learning and Computer Vision Under an Ecological Framework

Individualizing athletes' training programs can facilitate long-term training efficiency (performance improvement per unit of training time) in both youth and adult athletes, with individual sports (i.e., gymnastics and diving) using this approach the most, and team sports the least due to a low player-to-coach ratio which can hinder athlete development (Sigmund & Güllich, 2022; Zabaloy et al., 2020). An athlete's training program must be individualized to offer specifically tailored and challenging tasks, recognizing that each athlete's learning and performance approach varies, as athletes learn and grow on an individual basis, leading them to develop individualized functional movement solutions to performance problems (Liu et al., 2006). In golf, a player's technique is dependent upon their morphology and anthropometrics, and failing to self-optimize movements can negatively affect performance (Baker et al., 2017; Horan et al., 2010). Compared to traditional approaches, HPE can non-invasively and in real-time or retrospectively provide meaningful performance data for support practitioners, therefore allowing practitioners to avoid the pitfalls of a one-size-fits-all approach to athlete development. When analyzing an athlete's movement patterning, practitioners from multiple subdisciplines may be involved (i.e., coaches, performance analysts, developers, skill acquisition specialists, biomechanists, and strength and conditioning trainers), with each using domain knowledge and technologies to contribute different interpretations and insights into performance solutions (Reid et al., 2004). The communications of problems that may arise in an athlete's development may be a challenge as all members of the multidisciplinary team have their own ways of communicating typically based upon their domain specific language which can be misinterpreted by others. The ecological framework (see Figure 3) promotes a DoM which can encourage the sharing of experiential and empirical knowledge using common principles and language. This organizational structure can help integrate effective individualized athlete performance assessment, enriched with ML and CV technology. For example, coaches, performance analysts, and skills specialists have worked together to design individualized practice tasks in Australian Rules Football, using key principles from ecological dynamics (i.e., constraints led approach and representative learning design) (Browne et al., 2019; Woods et al., 2019).

The effect and nature of injuries are also highly individualized and in professional sports cost organizations money. Such financial pressures may lead to the rushing of recovery processes that may lead to severe longer-term injuries which can have irreversible effects on performance (see Figure 4, next page). ML approaches to data analysis can analyze large amounts of fitness and performance data in minutes and provide recommendations to practitioners allowing them to tailor training programs to reduce injury risks (Rajšp & Fister, 2020). For example, Oliver et al. (2020) showed how, using ML, it is possible to predict overuse injuries in athletes, while de Leeuw et al. (2022) demonstrated how in-season injuries could be predicted for youth football players. To predict injuries most accurately, ML algorithms require qualitative data (e.g., wellness questionnaires) and quantitative data (e.g., biological, and hormonal markers and fitness data) which support close collaboration between sub-disciplines of sports and computer sciences (Jain et al., 2020). In a functioning DoM considering the performance preparation of female athletes, for example, developers can create algorithms to track cycles, performance analysts can provide training load data, psychologists can provide wellness questionnaire data, while physiotherapists and physiologists can contribute hormonal data, thus allowing the coach to adjust an individual athlete's training load to reduce the risk of injury on an individualized understanding of each athlete's menstrual cycle.

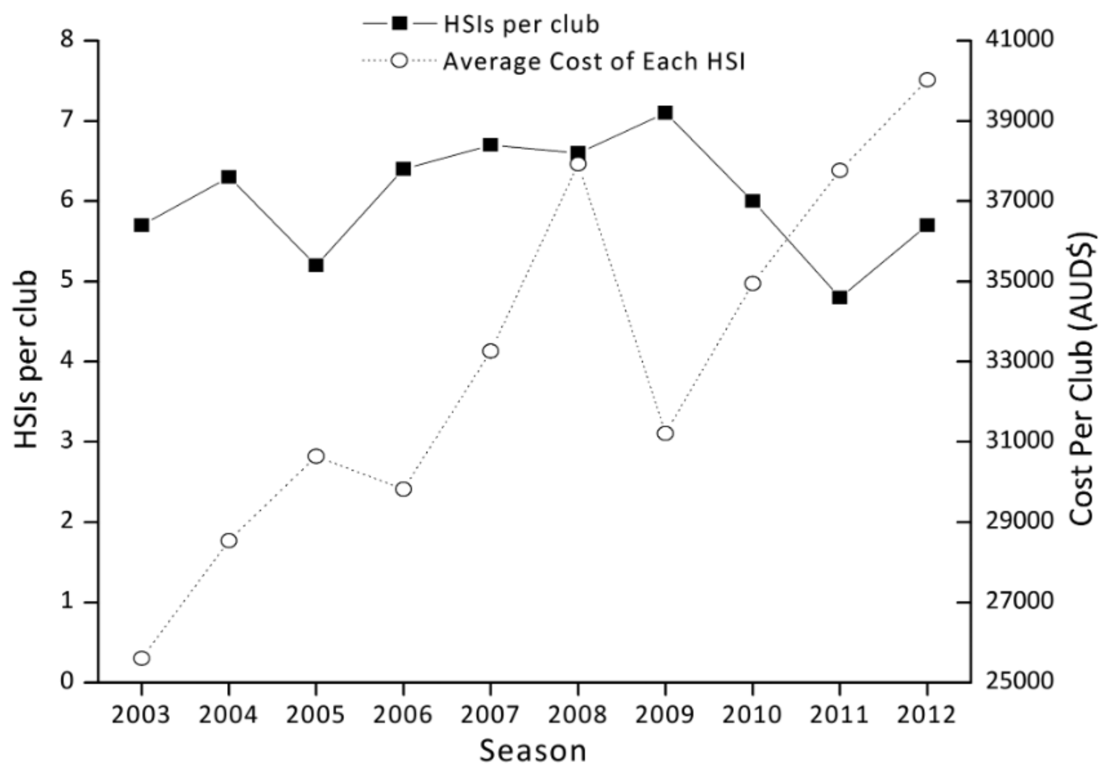

Figure 4. The average financial cost of hamstring injuries (HSI) across multiple seasons in the Australian Football League (from Hickey et al., 2014)

Enhancing Coaching Feedback with Machine Learning and Computer Vision Using an Ecological Framework

Providing athletes with feedback is a key part of the athlete development process, but providing feedback incorrectly can have negative effects on athlete development (Akenhead & Nassis, 2016). Athletes receive feedback from their coach and their environment. Research suggests that the best form of feedback athletes can receive is intrinsic feedback (i.e., the internal feeling of a movement within their environment) which allows athletes to self-regulate and find their personalized individual movement pattern. In contrast, extrinsic feedback (i.e., direct feedback from the coach) has been shown to hinder the athlete development process (Newell, 2003) by impeding intrinsic feedback. For example, if a football coach wanted to improve their athletes' short passing skills, rather than playing on a full-sized pitch and simply instructing players to work on short passes, they can reduce the size of the practice area so that only small passing options are afforded. Through this constraints manipulation desired behaviors may be elicited, allowing athletes to gain more experience and intrinsic feedback.

However, the introduction of technology (i.e., video feedback, quantitative feedback, and ML or CV) into an athlete development program typically creates explicit feedback. For example, the Toronto Raptors have developed a ML and CV system that provides explicit feedback on shot variables in real time to players during training, but this information is not present during a match (Shankar, 2022). Large amounts of extrinsic real-time feedback during or after performance can lead to an over-reliance on external sources for feedback, reducing an athlete's willingness to self-assess and regulate their performance, with long term negative effects (Chiviacowsky & Wulf, 2002; McCosker et al., 2022). This approach is also attributed to "over-coaching" which reduces coach-athlete interactions, shifts the performance evaluation to the athlete all of which can have negative effects on the athlete development process (Davids et al., 2007; Larsen et al., 2012). When providing athletes with feedback enhanced by ML and CV technology, practitioners should also consider the 3-skill learning stages (i.e., coordination, skill adaptability, and performance training) as athletes at different stages of development benefit from different types and frequencies of feedback based on varying needs, expectations, and preferences (Coté et al., 2010; Klatt, 2020).

The ecological framework (see Figure 3) can support the integration of ML and CV technologies into athlete development programs to enhance coaching feedback by supporting the collaboration between practitioners using key principles from a DoM (i.e., communicating experiential and empirical knowledge through shared language and principles). It also supports the design of information-rich practice environments enriched with ML and CV technologies, providing coaches with the support required (i.e., collaboration with developers) to gain a better understanding of their athlete's performance using ML and CV technology while enhancing the quality of feedback an athlete receives (i.e., using research-based approaches for feedback provision). One strategy in golf could involve using a ML system to analyze shot data and HPE system to analyze movement during a chipping-onto-the green practice task on the golf course. The approach would allow coaches to work with the golfer and change the topography of the shot, providing different informational constraints after each shot like the experience of the athlete during competition. Collaborations with developers provides practitioners (e.g., coaches, physiotherapists, biomechanists, and fitness trainers) with highly detailed performance feedback which, combined with a coach's domain knowledge, can be augmented for the athlete in a way that promotes their search for intrinsic feedback to find their personalized swing optimized to changing contexts on the course (Davids et al., 2017)

Future Research Recommendations

This position paper provided an initial step of rationalizing and supporting applications of ML and CV in sport. However, we suggest several approaches to empirical examination of this ecological framework. This ongoing process of methodological design and research is needed to ascertain how developers can enhance training tasks in practice. Therefore, it is important to see the effects on athletes and coaches when ML and CV are applied using the ecological framework. Sports have unique performance constraints, and diverse applications of ML and CV in athlete development programs are needed to evaluate potential in each use case. Finally, to our knowledge, no study has attempted to assess the performance differences that occur after the longitudinal implementation of ML and CV (i.e., with or without theoretical rationale) which could promote future applications if found beneficial.

Conclusion

This position paper has outlined how an ecological theoretical framework can enhance athlete development and performance preparation by rationalizing and supporting the application of ML and CV technology. The framework can guide collaborations between practitioners to create enriched practice environments. Three key areas in which an ecological framework could enhance athlete development programs were identified: (1) improving the design of practice environments, (2) allowing practitioners to provide an athlete-centered approach, and (3), enhancing the quality of coaching feedback with ML CV technologies for athlete development and performance preparation.

Authors' Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that the research reported in this article was conducted in accordance with the Ethical Principles of the *Journal of Expertise.*

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