Precision strength training:
Data-driven artificial intelligence approach to strength and conditioning

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In strength training, personalised strength training (autoregulation) approaches have been used to individualise exercise programs with monitoring for dynamic adjustment based on the individual response to training. While this transition from tradition-based training to evidence-based training framework has been an improvement in training practices, we argue that the future of strength training will also incorporate deep learning models powered by data. We refer to this data-driven framework as *precision strength training* inspired by the similar modeling frameworks used in precision medicine. In contrast to current personalised training in which the acquired athlete data is often subject to human expert decision-making, we are anticipating the rise of human-in-the-loop systems with an augmented coach who will be doing decisions collaboratively with the machine. Similar to other precision frameworks, such as precision health, we envision such a future to take decades to be realised and we focus here on practical short-term targets on a way to long-term realisation. In this chapter, we will review the measurement technology needed for continuous data acquisition from an individual during training/physical activity, how to acquire these datasets for the development of such systems and, how a proof-of-concept system could be developed for powerlifting training with applicability to general strength and conditioning (S&C) and physical rehabilitation purposes. Additionally, we will evaluate how the user experience (UX) of the system feedback and visualisation could be designed.

Keywords: *artificial intelligence, machine learning, deep learning, precision medicine, resistance training, strength training, precision strength training, strength and conditioning, powerlifting, physical rehabilitation*

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I. INTRODUCTION AND BACKGROUND

The massive amount of sports data generated has enabled the use of more and more powerful artificial intelligence (AI) models for the analysis of individual athlete performance, team play strategies and fans engagement [28, 126, 242, 713, 715]. For example, Christina Chase from MIT Sports Lab argues that: "data is the currency by which competitive advantage is won and lost. Those who find creative ways to unlock and harness it — will be the champions of tomorrow' [126]. Despite *big data* having been extensively used for in-game decision making in professional sports leagues, the sports business as a whole is lagging behind other industries in their use of data, as Sascha Schmidt puts it: "With all the excitement for sports, however, we cannot neglect that, from a business perspective, sport is one of the most conservative industries on the planet'.

The use of data in strength training (S&C) is has been very limited, partly due to the lack of suitable measurement technologies (see figure 1 later) that would allow continuous high-quality measurement without being too cumbersome for the athlete [882]. Nowadays, the strength training protocols are based on practical/clinical experience and evidence-based approaches with current evidence however, being sparse. There is a need for further advancement towards more more quantitative strength training frameworks integrating objective physiological measures with subjective measures, going beyond one-size-fits-all models. This framework introduced in this review is referred as precision strength training, inspired by recent advances in precision medicine.

Precision medicine, sometimes referred as personalised medicine, aims to quantitatively model the intra- and inter-individual variability of patients in response to treatment [152] (see figure 1).

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The concept of personalising care to the patient is not new, but recent advances in large scale databases, better measurement technologies, and computational tools, such as deep learning, are making data-driven precision medicine realistically achievable [432]. Data-driven precision medicine however has not yet become the clinical norm, requiring more clinical validation and model development for precision medicine to become one [15, 380, 761, 873]. The use of precision medicine framework for exercise prescription and monitoring is not new either. Buford et al. [99] described an "exercise as medicine' framework for general population, and Ross et al. [690] demonstrated a model that captured inter-individual differences in response to cardiorespiratory exercise, coining the term *precision exercise medicine*. Precision health is conceptually close to precision exercise, as it attempts not just to address the symptoms, but to promote and prevent diseases on a population and public health level [253, 313].

Early precision exercise medicine literature was focused mainly on quantifying inter-individual (between subjects) differences in intervention response and identifying responders/non-responders to exercise [36], with less work devoted on the role of intra-individual (within-subject) variations. This inter-individual focus was shown to erroneously suggest large inter-individual variation when not addressed properly in the experimental designs and statistical analysis [36, 144, 194]. In a study by Islam et al. [362], the athletes showed significant intra-individual variability to the same training stimulus, and the authors highlighted the fact that without the use of repeated trials, some of the subjects could have been wrongly classified as high or low responders. In contrast to traditionally used net mean treatment effect in studies, one is interested in the individual responses [600] within precision exercise framework, and how measurement noise (that is random) can be disentangled from the inherent physiological response (that is reproducible) [361]. While there have been advances in statistical methods to analyse these heterogeneous responses [174, 801], the future studies need to consider jointly the research protocol design, measurement technologies, and modelling tools for disentanglement of sources and causal relationships [761, 776, 836].

In strength training, concept of *personalised training* (referred also as *autoregulation* [276]) has existed for some time, in which the training load and recovery status of an individual athlete are continuously monitored, and the exercise continuously adapted by a human coach (subjective decision making) using the monitored parameters output [61, 135, 537]. The scientific challenge in practice with this framework has been the proper parametrisation of 1) the training load [40, 55, 654, 883]; 2) the recovery state and preparedness to train [322, 394, 537]; 3) injury risk prediction [356, 357, 601, 755, 881]. Out of these three goals, training load and recovery state are within practical reach at current technological maturity level, whereas injury prediction seems overly challenging [315, 356, 357, 385, 386, 599, 678][1], mainly due to inherent low prevalence of injuries in athletic population [101, 105, 344, 377, 397, 627, 686, 743, 878], which subsequently leads to injury prediction models with poor predictive power [348, 504].

In precision medicine literature, personalised and precision medicine are sometimes used interchangeably, where in this review the "precision' in precision strength training framework refers to the dynamic data-driven training program individualised for each athlete, and updated dynamically based on the 'precision biopsychosocial model'. The definition of autoregulation (personalised training) framework is relatively ambiguous in the literature [276], and the approach described in this review fits to existing loose definition, but we wish to stress the quantitative modeling aspect with our precision prefix, inspired by the precision medicine literature. In brief, precision medicine is interested in developing disease progression models [902], prescriptive modeling with individualised treatment effects [78, 141, 473, 625], phenotyping patients [593, 832, 866], and acquiring patient similarity measures [729].

Transferring these tasks to the strength training context (see figure 1), the training progress can be interpreted as the disease progression *trajectory*, the changes in training program and active recovery interventions as medical intervention/individualised medical treatments, and the clustering/phenotyping athletes based on their response to training, e.g. machine learning recommender system for sports [254, 574] with recommendations like you "athletes with similar trunk:thigh ratios cannot squat as upright'.

The personalisation in strength training, is typically based on subjective measures for daily preparedness and logged training loads, with training adjustments done subjectively by either human expert [210, 276, 392, 875], or by non-learning mathematical methods [104, 231, 328, 329, 343, 597, 749]. A practical commercial example of the mathematical modelling approach for strength training is the JuggernautAI® system (https://www.jtsstrength.com/product/powerlifting-a-i/), which first surveys basic athlete characteristics, then designs training periodisation and updates the program dynamically based on the logged progress of the athlete. This type of system can be seen as an upgraded training diary/logger with more advanced training

[1] Sam Robertson's tweet, Aug 2, 2019 twitter.com/robertson_sj/status/1157188689702707200

feedback [509, 804], examples of traditional loggers are Gravitus® (https://gravitus.com/), Strong® (https://www.strong.app/), gymaholic® (http://www.gymaholic.me/). These consumer-level train loggers do not typically handle aggregation of objective measures (see section §III later), and their use for advanced data-driven training modeling is somewhat limited.

In larger professional sports organisations, more advanced athlete management systems (AMS) [268, 541] are used instead these consumer-level training diaries. For example, Smartabase®, an AMS developed by Fusion Sport® (https://www.fusionsport.com) integrates electrical medical records (EMR) [789] and athlete performance data with the possibility to develop multimodal models while managing of multiple athletes. Such systems are used by various professional sporting organisations ranging from UFC® Performance Institute [471] to The Royal Ballet (UK) [180]. At present, athlete management systems lack interoperability application programming interface (API) standards [642] such as the one developed for healthcare, like the HL7 FHIR version 4.0.1 introduced in USA starting from 1st January 2021 [568, 705, 812]. Many vendors such as Kinduct® , Smartabase®, Edge10®, Kitman® and BridgeAthletic® have though formed partnership allowing cross-vendor aggregation of athlete data [2].

Precision strength training is similar to *precision physiotherapy* in which the physical rehabilitation program (e.g. after an orthopaedic surgery or a stroke) is being individualised to the patient with data-driven deep learning models and gamified therapy [86, 463, 496, 785, 885]. In United Kingdom an interest group called "Digital and Informatics Physiotherapy Group (DIPG)" (part of the Chartered Society of Physiotherapists, CSP) was formed to develop, evaluate and promote was formed to promote the use of novel technologies such as virtual reality (VR), telerehabilitation and AI in clinical physiotherapy. Having possibility of patients exercising at their homes with automatic real-time exercise feedback [161, 173, 209, 294, 477, 538, 595, 674, 675, 704, 815] could positively influence exercise adherence leading to improved patient outcomes and lowered healthcare costs [445, 884]. Similarly, these personalised and gamified approaches could be designed for general population as a preventive health measure [825], for example to increase the uptake of resistance training [63, 867], as 80% of European adults do not meet the global resistance training guidelines of 2 or more days of resistance training per week [62].

[2] https://blog.bridgeathletic.com/integrating-your-tools

As precision strength training does not yet exist as an established field, we derive the concepts in this review from literature on evidence-based personalised strength training[562], precision physical rehabilitation [885], deep learning [873] and sport science [126, 653, 677], to give the readers an overview of plausible future scenarios in strength training. We will review the challenges involved in the development of precision strength training framework by going through the relevant sports measurement technology, dataset requirements, strength training theory and service design for relevant for deploying the system to be used by the patient, clinicians, athletes and their coaches, in an effort to try to bridge the gap between in-lab theoretical sports science and real-world deployment [97, 529, 531, 865].

In this review, we refer to three generations of strength training systems: 1) tradition-based training, that is often referred as practical or clinical experience, and is the tacit knowledge gained by the practitioners; 2) evidence-based training, that is based on scientific strength training studies with relatively narrow inclusion criteria applicable to specific populations and set of assumptions. The intra- and inter-individual variability is mitigated by selecting relatively homogeneous populations; 3) data-driven precision strength training, that uses broader inclusion criteria and attempts to model the exercise responses of a larger heterogeneous population. The intra- and inter-individual variability in response to training is learned from the acquired using multivariate (high-dimensional) AI models.

We will envision strength training and sports management to follow the advances in medicine and society as a whole, with the trend for increased human-machine interplay in human-in-the-loop systems, that are developed augmenting human experts rather than by replacing them with AI [49, 258, 279, 310, 615, 742, 753]. It is not trivial to transfer and quantify the tacit knowledge from athlete-coach to be used for quantitative modelling [81, 482, 588], and the "$n = 1$" expert knowledge need to built into these precision strength training frameworks [332, 442, 478, 566, 634, 722, 740, 831]. Eventually, over the coming decades, the more conservative "non-tech" strength training coaches will be re replaced by the strength training coaches embracing AI, as it is projected to take happen for example to radiologists [721].

The review has been written with a focus on machine learning practitioners, who are familiar with mathematical modeling concepts, and less with strength training and sports science domain knowledge [616, 677]. We take a systems-level approach in this review [33, 64], covering measurement technology, basic modeling concepts, dataset requirements and user experience in future quantitative strength training systems [145, 850], built on top of the evidence-based strength training research [563]. Less emphasis is placed on the recent emerging exercise physiology concepts such as "network physiology of exercise' that is a system-level approach on how physiological states emerge from complex nonlinear interactions within human body [44]. In general, we would hope that this review is a good starting point for data scientists, entrepreneurs and sports scientists understanding the main challenges in strength training modelling, as often in digital health, solutions are developed for non-existing problems [483, 525].

II. FROM PERSONALISED TO PRECISION STRENGTH TRAINING

In this review, the term personalised strength training refers to the current evidence-based strength training practice [562], where athlete are being monitored with some sensor technology, but majority of the training intervention decisions are being made by a human expert (e.g. a coach or a physiotherapist). The existing quantitative frameworks, for example for injury prevention and prediction, are not the most useful at the moment for expert-level coaching [356]. In practice, there are no quantitative frameworks augmenting coaching decision, and human coaches are often overwhelmed by the various training load and recovery metrics, and often fall back on more conservative evidence-based or practical experience measures [406, 601]. This is especially true in strength sports such as in powerlifting, in which the practitioners often resort to trial and error approaches, as evidence-based protocols are lacking [821]. None of the suboptimal quantitative frameworks, such as acute:chronic workload ratio (ACWR) [20, 851], are truly data-driven and are rather more conceptual models. There have not been any major artificial intelligence studies to the authors' knowledge for strength training research, with the few studies using machine learning have used small datasets mostly for proof of concept studies, and not for real-world deployment [653].

Strength training (or S&C) can be broadly defined by three types of training goals: 1) maximal strength production (e.g. powerlifting) [563, 912]; 2) hypertrophy training to increase muscle mass (e.g. bodybuilding) [364, 379, 716, 750]; 3) rate of force development (RFD), the production of explosive strength for example in Olympic weightlifitng, boxing and track and field sprinting [197, 603, 717, 829]. In practice, a mixture of the goals are present, especially in non-strength sports, in which for example both muscle mass and increased maximal strength might be desired (e.g. American football), and in weight-class sports such as boxing, explosive strength might be desired without the added muscle mass. In these cases, the monitored metrics should be adjusted accordingly to the specific sports in question [308, 322].

The need of sports-specific measure is highlighted for example by the possible counter-intuitive effects of hypertrophy to strength levels described in recent research. Reggiani et al. [664] showed that the increase in muscle mass did not necessarily lead to increase in strength and vice versa [664], and in worst case, the increase in muscle mass was shown to decrease strength production [664, 718]. There also seems to exist multiple types of muscle hypertrophy [664, 820], with the concept of task-specific hypertrophy [820] becoming relevant when trying to transfer the gains from strength training program to improvements in the particular sport of the athlete [906]. For instance sports as different as combat sports [485, 765] and ballet [16, 180, 818], can be benefited for similar plyometric/ballistic training for explosive force production [906] mixed with some maximum strength training. Whereas in sports like pole dancing that do not require explosive strength, benefit more from powerlifting-type maximum strength training [874]. In circus training [293, 435] and in throwing sports [82, 340], more emphasis should be put on warming tendons and ligaments properly, and making sure that the tendons adapt to training and do not fall behind from faster muscle strength adaptation [387].

One-repetition maximum (1RM) is probably the most commonly used tool at the moment to personalise strength training programs [810]. Athlete's training loads are programmed using some percentage of 1RM, e.g. at week 1: 3 sets of 5 repetitions at 60% of 1RM, week 2: same at 70% of 1RM, and so on. These percentage progressions are typically programmed using some tradition-based values, that the practitioners have found effective in the past, using training cycles of various lengths. This splitting of training to cycles is referred as periodisation often involving the following concepts: macrocycle (e.g., 1 year between the main competition of the athlete), mesocycle (e.g., 4 weeks), microcycle (e.g., 1 week) and individual training sessions. For example in powerlifting, the goal of macrocycle, is to increase the 1RM of the athlete as much as possible, while monitoring the progression of 1RM during that macrocycle [40, 763, 819]. In practice, proxy measures need to be developed for this progression monitoring, as the athletes are not often programmed to lift 100% of 1RM very often, as such heavy loads during training season are seen counterproductive for the overall progress and needlessly increasing the risk of injury. Thus, one wants to find a balance between of not overtesting the athletes, without the test measure possibly coming the goal itself [40, 699], and not undertesting the athletes and not without being able to track the training progress [819].

Research has been devoted for finding indirect (*proxy*) measures for the 1RM progression, with no conclusive measure for strength training. For

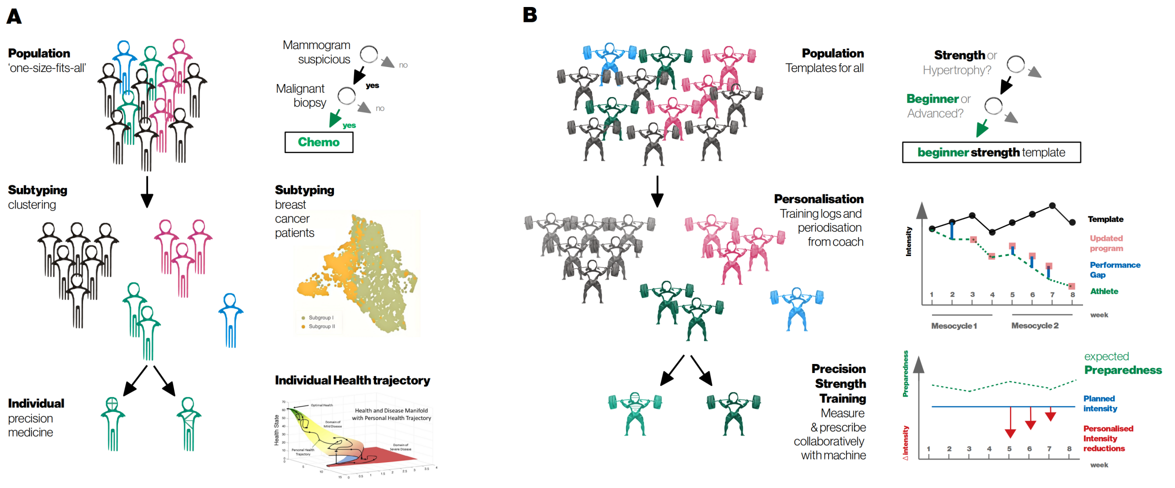

Figure 1. Precision medicine vs. precision strength training. (A) Simplified model of traditional 'one-size-fits-all' medicine uses simple decision rules for treating all patients the same [168], whereas precision medicine attempts to tailor the treatment based on different subtypes [455] or individualise the treatment based on the individual patient [181]. The health states on the three-dimensional trajectory manifold in strength training can be interpreted as progress, the athlete needs to have the peak performance (health state) in competition, and optimal decisions need to be taken to get there. Some decisions on the manifold takes the athlete only sideways, i.e. performance is plateauing despite the modifications to training. Note that both subtyping and health trajectory are visualised with dimensionality reduction techniques such as t-SNE or UMAP to make high-dimensional nonlinear models human interpretable [43, 423, 517, 782]. (B) In strength training, the equivalent to one-size-fits-all approach are the training program templates offered often online with little customisation to the athlete [443]. Personalised strength training (or autoregulation) is often done with a coach who updates the program for the athlete [169]. In our simplified example, two training mesocycles are shown, in which the athlete is able to do the programmed exercises on week 1 but fails to do so on week 2. On week 3 the programmed loads are dropped to the levels of week 2 [321], and the athlete is able to keep up with the programming during the first mesocycle. During second mesocycle, the athlete shows overtraining syndrome, and keep up with any of the programmed loads ("performance gap'), except on the week 4 that is a *deloading* week. In our simplified precision strength training framework, the level of training preparedness would be quantified, and overtraining symptoms could be reduced faster by reducing training loads (personalised intensity reductions) when the model has detected that the athlete has not recovered properly. The accuracy of such automatic adjusting obviously depends on the quality and availability of data for training such models as we review in this article.

example squat jump height (SJH) [819] and isometric mid-thigh pull (IMTP) [374] have been used as proxies for Olympic weightlifting monitoring; multiple repetition test [671], and mean concentric velocity (MCV) from load-velocity curve have been used for 1RM estimation in powerlifting [50, 862, 876]. Common problems with these testing measures is that the testing itself is too physically demanding requiring a recovery period itself [667], and that the athletes might become better in doing the proxy measures themselves during the monitoring period, i.e. there is a learning effect occurring, that can bias the measurements and increase the uncertainty in progression monitoring [763].

Conceptually, a more complete approach for performance tracking, is to use for example the acute:chronic workload ratio (ACWR) [358], that is based on classical fitness-fatigue model [106]. In ACWR there are *internal* and *external loads* [297, 355–357]. The external load is the prescribed exercise session, e.g., the training load and volume. The internal load corresponding to the training *preparedness* and recovery state, including all the factors influencing athlete's ability to recover, such as sleep quality [66, 136, 287, 480, 745, 844, 847], nutrition [26, 85, 112, 554, 558, 614, 750, 826], and overall stress in life [324, 365, 771], i.e. constituting for the biopsychosocial model of the athlete [319, 809]. The external load is easier to quantify with less uncertainty, assuming that the athlete is doing every workout with repeatable technique and focus ("exercise adherence") [810, 926]. The ACWR as a quantitative model however does not seem to perform at a satisfactory level, and in practice expert judgement is preferred over its predictions [356], thus the key idea of the precision strength training framework is the development of a quantitative biopsychosocial model that would help to explain the observed intra- and inter-individual variability responses to training programming [280].

There is an ongoing transition from tradition-based strength training, so-called 'bro science' in gym jargon [2], to evidence-based strength training [563, 716], with some strength & coaching coaches resisting this cultural change [2]. Some scepticism to evidence-based training is warranted, as

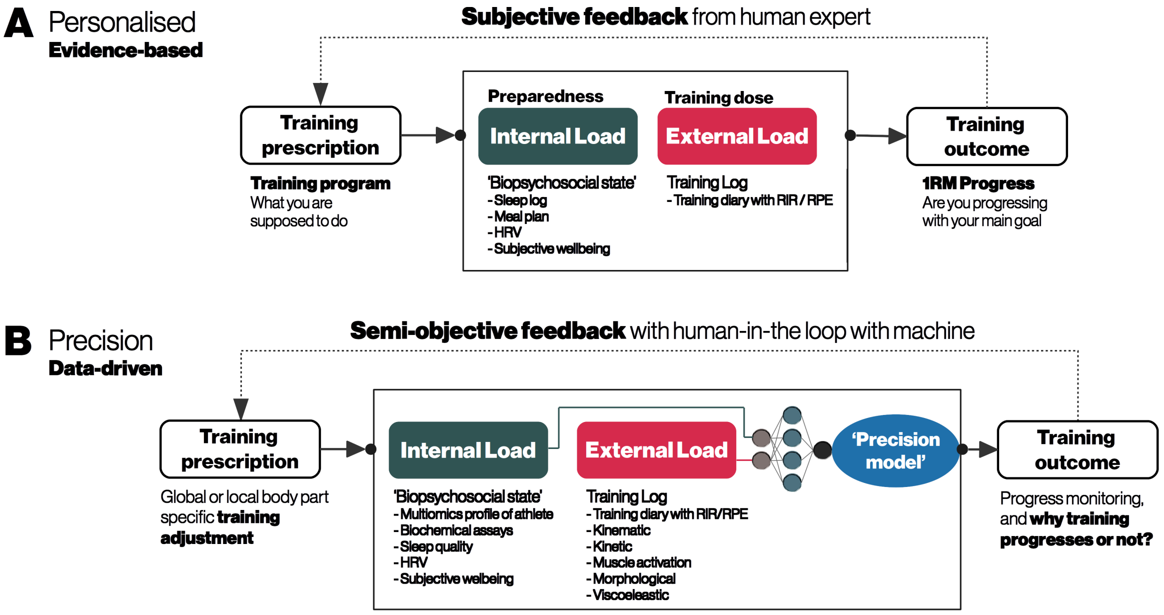

Figure 2. (A) Personalised (evidence-based) strength training [276, 563, 629] in which the human coach interprets the process and makes the decision for the athlete being guided by science [2], using some tradition-based heuristics [169]. Some of the training is quantified for example in a form of training log with subjective rating of perceived effort (RPE) or reps in reserve (RIR, and mathematical models can be developed from them. The dose-response to training prescription depends on the athlete's internal load [280, 324, 327, 355, 507], that is not often captured quantitatively by the existing frameworks such as acute:chronic workload ration (ACWR) [357]. (B) In idealised future, the precision strength training framework built top on evidence-based training is able to quantitatively measure and model both the internal and external load and adjust the training and recovery activities accordingly collaboratively with the coach.

several gaps between the theory and practice in strength training research exist due to the field being so small, and therefore, practical coaching decision thus often requiring a lot of improvisation around the fragmented evidence. Evidence-based medicine (EBM) has faced similar resistance to change from its inception in the early 90s [89, 221, 421, 514, 548], with some clinicians stating that EBM has led to diminished acceptance of "the art of diagnostics" or personal clinical judgement [275, 454].

Similar resistance to change is felt with the recent early implementations of precision medicine [15, 696], both at the organisational level [696] and at the scientific level in terms of implementation readiness. For example, molecular profiling, clinical risk modelling and pharmacogenomics (PGx) are more mature and closer to broad implementation compared to less understood genomic EHRs and disease subtyping [15]. The overselling of model such as ACWR [356], can have its analogy in computer-aided detection (CAD) for mammography in breast screen screening. The CAD models were constantly underperforming compared to human readers [304], leading to an increased cost of proofreading and evaluating unnecessary false-positive results [211], and eventual distrust of all algorithmic solutions. Recently, Ziegelstein coined the term *personome* in 2015 to describe the process of bringing back the person of the patient, and how the patient biopsychosocial state with quantitative measures modulate their response to treatment [931]. This is similar to our vision on how in precision strength training framework, the full biopsychosocial model of the athlete is formulated in more quantitative framework.

III. MEASUREMENT TECHNOLOGY FOR PRECISION STRENGTH TRAINING

We will review here the most commonly used measurement technologies for monitoring athlete's strength performance.. The cost and size of high-end motion capture systems have traditionally constrained the use of these technologies in field studies and outside the sports science laboratories. With emergence consumer devices such as Microsoft® Kinect™ re-purposed for sports science, the cost of technology has become less of an issue [14]. Recently interesting developments in wearable compressive garment-based sensor platforms [286] and novel sensors/actuators developed for extended reality (XR) [383, 854] and soft robots applications [738] are enabling the design of future non-invasive and cost-effective continuous performance monitoring solutions for strength training.

The development in sensor technology and its ease of use might refine the definitions of the testing (done infrequently) vs monitoring (done often) variables used by some S&C coaches [667]. Some of the measures such as blood sampling and dual-energy X-ray absorptiometry (DXA) currently seen as testing measures might become monitoring measures with the introduction of low-cost and accurate future alternatives [252, 303, 333, 456, 462, 633, 814]. Some functional test measurements such as isometric mid-thigh pull (IMTP), might be replaced with something less physically demanding to make their use more frequent as a monitoring measure. While often in functional testing, it is the simplest to use some of the main exercise movements, such as bench press or squat, at the end of each mesocycle for progression monitoring, without increasing fatigue levels of the athlete [363].

Similarly, the more athlete-friendly sensor technology could make monitoring more time-efficient and better integrated to training routines. This especially applies in team sports in which athlete-level monitoring is sometimes challenging [766]. Future studies should also look into developing a proper "sports economics' frameworks, inspired by health economics [42, 127, 151, 569], which would include the time and financial cost of given measurement technology compared to its expected value for athletic performance.

Easily acquired continuous measurements are not always helpful when the signal has low fidelity, or when the data is not the most relevant for the task in question [113]. Example of consumer-level large-scale data acquisition can be found from the "quantified self" (QS) movement, in which participants track their biomarkers as *biohackers* for data-enabled self-improvement [4, 175, 219, 528, 811]. Participants in QS movement do not always feel the measurement as source of motivation and entertainment as often portrayed [163], but rather feel anxiety from self-measurement and not being able to meet their goals [18, 52, 219]. Similar patient anxiety has been shown with recent digital health solutions, such as implementation of atrial fibrillation detection via smartwatches, that do not seem to offer high enough signal fidelity, leading to excessive false-positive diagnoses and incurring needless expenses and patient anxiety [621]. In contrast, continuous data acquisition with smartwatches seem to be useful for monitoring Parkinson's disease patients[637], helping the clinicians to track the symptoms and manage treatment better [8]. In practice, even at the highest signal quality, the measured variables cannot capture the athlete's whole biopsychosocial performance. Therefore, the inherent uncertainty in the combined measures should be taken into account when using the measures for decision-making [40, 299, 684], to avoid key performance indicator (KPI) fixation like ones seen in university evaluation systems [773].

Most of the recent products from digital therapeutic and sports analysis companies such as Kaia Health® (https://www.kaiahealth.com/), Fitcus® (https://www.fitcus.com/), Curv Health® (https://www.curvhealth.com/), and Kinetisense® (https://kinetisense.com/) rely on unimodal kinematic video data, either using a standard smartphone camera or by the company-produced custom camera. Whereas companies such as Figur8® (https://figur8tech.com/) has chosen to complement their inertial measurement unit (IMU)-based kinematic data with muscle activation data from a mechanomyographic (MMG) sensor, for a multimodal measurement of the athlete behaviour. These business choices have been partly driven by consumer expectations of a delivery via smartphone apps, and the longer development times associated with new hardware development favouring software solutions over hardware solutions [68]. We hypothesise that smartphone-based kinematic data might not be of sufficient quality for training precision strength models, to obtain good enough *actionable insights* [754, 930], to surpass or augmenting well the human expert opinion. However, eventually with large enough multimodal datasets acquired, precision strength training models could be trained with multimodal datasets, and deployed then to be used only with video data, and to approximate the missing modalities such as kinetic data, from the unimodal kinematic data alone [139, 250, 376, 657].

A. Kinematic: Motion Capture and Pose Estimation

Motion capture (mocap, mo-cap) refers to the quantification of movement patterns of objects (e.g surgical tools), animals, and people [58, 527, 712, 796]. In sports and rehabilitation applications, the study of these biomechanical measurements are often referred as movement science [269, 769]. The estimated human pose from video or sensor stream [923], is typically encoded as a skeleton pose sequence that is a time series of three-dimensional joint locations [298, 444, 493] (see figure 3). The technical details on how video, sensor, radiofrequency (RF) or point cloud data is transformed into skeleton sequences is beyond the scope of this review, and the interested readers are referred to following works [345, 372, 617, 645, 898].

The choice of the deep learning approach for modelling skeleton sequences, is typically based on graph convolutional networks (GCNs) [736, 916], where the nodes of the graph represent the 3D joint locations, and edges of the graph represent the bone connecting the joints. In addition to this basic joint-level encoding, one can encode additional features on the graph (if acquired) on the edges and nodes of the graph [492, 632, 736]. For example muscle stiffness and muscle activation are useful in strength training and can be encoded on

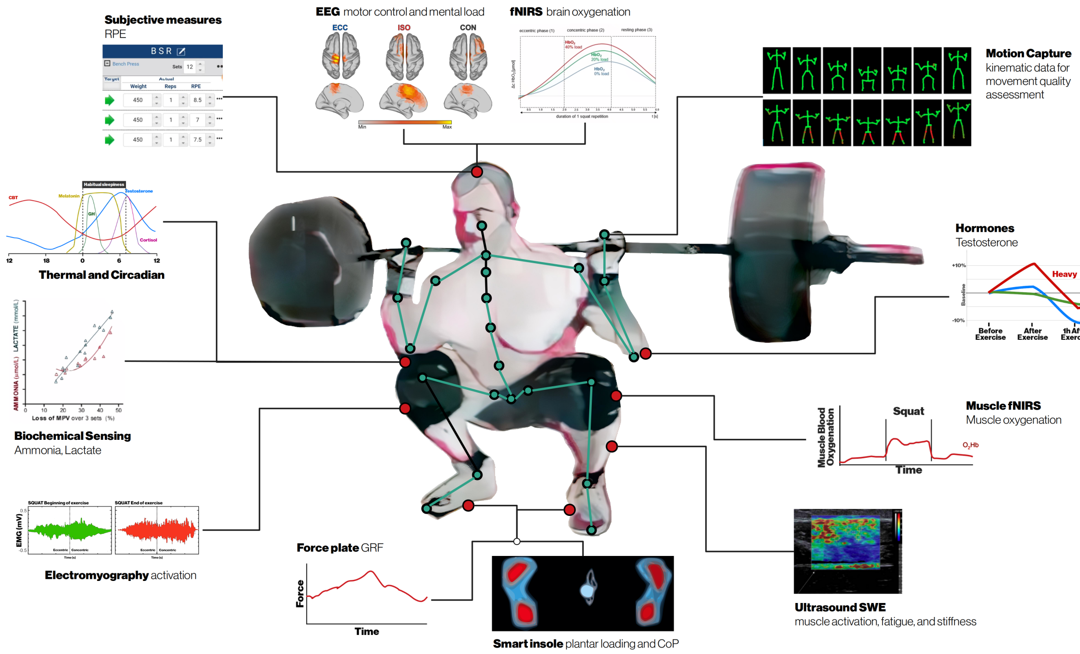

Figure 3. Example set of measurement modalities useful for developing precision strength training frameworks. Motion capture (kinematic) data for movement quality assessment [607], testosterone assay for both acute exercise-induced response and global levels [288, 484], muscle oxygenation with fNIRS [679], ultrasound SWE for the (real-time) quantification of musculotendon stiffness [419, 467], cartoon of smart insoles for quantifying center-of-pressure (CoP) and the *tripod loading* , force plates for measuring ground reaction forces [245], EMG for measuring "activation" [257] ("myoelectric activity" more exactly [841]), sweat-based biochemical sensing for detecting metabolic and neuromuscular fatigue from ammonia and lactate levels [697], core body temperature for circadian phase [788] and muscle temperature measurements for training preparedness, subjective rating of effort through RPE logging (https://www.reactivetrainingsystems.com/), cognitive load from electrical (EEG) [396] and hemodynamic (fNIRS) brain activity [395]. Image from Dr. Ben Pollock, reproduced with permission. *fNIRS functional near-infrared spectroscopy, SWE shear-wave elastography, RPE rating of perceived effort*

the edge of the graph; tendon stiffness and range of motion (ROM) can be for example encoded on the node of the graph.

The GCN formulation also allows to use traditional signal processing techniques such as dynamical mode decomposition (DMD) and Koopman operator [503, 561, 892] to approximate nonlinear human locomotion with a computationally simpler linear system [247]. However, recently neural ordinary differential equation (ODE) based models have shown to be a more versatile approach compared to DMD, with better intrinsic handling of missing and irregularly sampled data [132, 780, 901]. Additionally, graphs (single athlete) can be embedded into larger graphs (e.g. team of athletes in a basketball game), if one would be interested in how group dynamics (e.g. basketball game) affect the individual biomechanics [248], or vice versa.

There are a variety if different motion capturing technologies including low-cost inertial measurement units (IMUs) [619, 680], wearable cameras ("egocentric pose estimation') [179, 350, 489, 502], smartphone cameras [497, 539, 643], Kinect^{TM}-type depth cameras [14, 102, 148, 626], and high-end motion captures system such as Vicon^{TM} or Optitrack^{TM}, with the prices of high-end system reaching up to to $200,000 [808, 817]. Different technologies offer different spatial and temporal resolutions, and make different tradeoffs in terms of performance and cost. For example the spatial accuracy of joint locations is especially relevant for tracking very subtle changes in movement patterns [575, 728], and high temporal resolution is desired for fast-paced sports such as mixed martial arts (MMA) [907]. The choice of used technology ultimately depends on the application, but for our strength training application in advanced athlete population, we are more interested in spatial resolution than temporal resolution. As highlighted by Seethapathi et al. [728] for movement science research, the off-the-shelf deep learning models such as OpenPose [109] trained on generic movement datasets such as NTU-RGB 120 [486] might not provide good enough spatial joint locations highlighting the need for custom dataset acquisition (see IV C below).

The video-based motion capture systems offer a higher spatial accuracy compared to low-cost IMUs, that are based on sensing changes in gravity (accelerometer) and rotation (gyroscope) [680], and converting those measures into estimates of human movement. IMUs offer higher temporal precision at lower cost compared to cameras. Additionally in contrast to cameras, the IMUs can be worn by the athletes as a smart compressive garment [411, 893], developed for example by companies such as Xsens^{TM} (https://www.xsens.com/), Cape Bionics^{TM} (https://www.capebionics.com/) and Teslasuit^{TM} https://teslasuit.io/. The wearable compressive garment is relatively invisible to the athlete, but the technology has not gained the market traction as hoped by the companies and practitioners [155]. IMU-based systems additionally can be used for continuous measurement [663] when longitudinal trends and day-to-day fluctuations in movement patterns are of interest [172]. The challenges with the use of IMUs is their time-dependent drift [868], soft tissue artifacts due to skin motion in relation to underlying bone [236, 460, 909], and the need for complicated calibration making their use cumbersome [71, 803, 868]. Recently, low-cost alternatives to IMUs have been developed, such as strain sensors embedded in knee braces [262], and as electronic skin sensors for monitoring lumbar-pelvic movements [919].

B. Kinetic: Force measurement

The kinematic data only quantifies the biomechanics of athlete performance, e..g the squat movement pattern [607] but does not tell anything about the forces produced by the athlete, for which we need to measure the kinetic data [413]. Multiple technology options exist for kinetic data measurement including low-cost *smart insoles,* Nintendo Wii Balance Board, and high-end "gold standard force plates for kinetic data, that can be used to derive ground reaction forces (GRFs), rate of force development (RFD) and centre of pressure (CoP) parameters. In sports performance laboratories, the force plates are routinely used [526, 759], but recently low-cost insoles [195, 250, 378, 612, 795, 864] and Nintendo® Wii Balance Board^{TM} [543] have been investigated as alternatives as the cost of force plates can be prohibitive in some cases. Recently, non-learning mathematical [863], and deep learning models have been developed to approximate the forces generated by the athlete, solely from non-kinetic measurements, such as from kinematic data [323, 375, 724]. These approaches naturally require development datasets with the both modalities (kinematic and kinetic) in order to validate the approximation accuracy of the model when deploying to real-world use just with the kinematic modality.

C. Muscle activation measurement

In addition to the kinematic and kinetic data, strength training research is often interested in how and when muscle is activated/recruited during movement [261], when muscle experiences fatigue [513], and how different neuromuscular processes are involved in force production [415]. The most common measurement technology used for these purposes is surface electromyography (sEMG) [6, 73, 100, 115, 784, 841], that involves placing electrodes on top of the skin, either as individual single sensors or embedded onto a wearable smart compressive garment suit [189, 286, 411, 752, 896]. Kim et al. [411] studied the effect of garment fit, i.e. clothing pressure, to sEMG signal fidelity, and showed higher pressure led to improved signal-to-noise ratio (SNR) highlighting the need for customisation of smart garment. This has been applied in practice, for example by Cape Bionics^{TM} company, scanning the athletes in 3D (see e.g. [814]) and customising the suit from the scan to the given athlete.

There has been some controversy on the usefulness of EMG in strength training research [159, 216, 840, 841], with some people claiming EMG being totally useless for strength training [159], while some have argued EMG having still value given proper interpretation knowing the limitations [840, 841]. It has been acknowledged that one cannot infer from the EMG amplitude alone the number of the motor units recruited to complete a specific movement/task because the number will exclusively depend on the muscle group(s) being recorded [257]. Mesin et al. [544] for example showed that tibialis anterior has a superficial-to-deep recruitment pattern, causing the sEMG amplitude to rise faster than the force levels. This suggests that in some cases, both surface and intramuscular electrodes could be used simultaneously [924], for more complete view of the muscle activity. The use of sEMG seems always justified for studying the timing characteristics of muscle activation and deactivation, information that could be used in musculoskeletal model simulations [464].

Vigotsky et al. [841] argue that one thus should avoid using the term "muscle activation" when referring to EMG amplitudes, and utilise terms such as 'myoelectric activity' or "muscle excitation', as sEMG measures changes in muscle fibers' membrane potential. Throughout this review, we use the more generic term 'activation' in broad sense for all the techniques aimed for measuring some sort of muscle activation/excitation. At the moment there seems to be no evidence suggesting that sEMG is suggestive of hypertrophy monitoring [296], nor there is really evidence to suggest that training load recommendations could be extrapolated from sEMG amplitudes [841]. More studies are needed to understand the training load programming and sEMG amplitudes [841]. Detailed review of sEMG intricacies is beyond the scope of this article, and interested readers are referred to the excellent review by Vigotsky et al. [841].

Furthermore, it is also possible to to use the intramuscular or surface electrodes to drive muscle activity, known as electromyostimulation (EMS) [229], neuromuscular electrical stimulation (NMES) [237], functional electrical stimulation [399], electrical muscle stimulation [220], or electrical dry needling [199]. In strength training, electrical stimulation can also be used to test the force production of muscles such as *m.* abductor hallucis (AbH) that are often hard to voluntarily activate [592]. Recently, sEMG research and technology development have been driven by human-computer interaction (HCI) field with the interest for hand gesture sensing [577, 854], from companies such as Facebook® that recently had acquired companies CTRL-Labs™™, a company who owned the intellectual property (IP) for the Myo™ EMG armband also used in exercise applications [431, 453, 479, 556].

Complimentary to electrophysiological sEMG, there are its "mechanical counterparts': mechanomyography (MMG) [790], force myography (FMG) [59, 891] and tensiomyography (TMG) [494]. They are similarly measured from the surface of the skin, while not commonly used in sports application, when done, they are acquired simultaneously with sEMG. Sonomyography (SMG) is an ultrasound-based "morphological counterpart' of sEMG [285, 692], and is also often measured simultaneously with other activation modalities for complementary activation information. Functional near-infrared spectroscopy (fNIRS) [535, 701] can be used to measure the hemodynamic muscle response to study muscle oxygenation behaviour [23]. Similarly to other complimentary methods, it is often used simultaneously with sEMG as recently demonstrated in a wearable suit designed for European Space Agency (ESA) space crews [188].

D. Muscle morphology and its viscoelastic properties

In addition to the kinematic, force and activation data, researchers are often interested in the morphology of the musculoskeletal tissues, i.e. its geometry, thickness, and stiffness. Ultrasound imaging (ultrasonography) is the most commonly used technology for measurement of muscle properties, due to its high spatial resolution and relatively low cost [813]. Ultrasonography can be augmented with ultrasound shear wave elastography (SWE) that enable continuous measurement of viscoelastic properties of musculoskeletal tissues [166]. SWE can be used to study the muscle stiffness after training session [830], Achilles tendon stiffness in natural environments using a wearable SWE [302], Achilles tendon stiffness and its effect on ROM in squat [270], dynamical muscle contraction during squat [571] with deep learning inversion [224], changes in viscoelastic properties of muscle during fatigue [119], and efficacy of stretching program [21, 240]. Myotonometry (MMT) is a low-cost alternative to SWE for assessing musculoskeletal tissue stiffness, that was recently used simultaneously with SWE to construct a 3D spatial map of muscle stiffness [419], and with TMG to measure neuromuscular response and muscle stiffness [452].

With the acquisition of kinematic, kinetic, activation and morphological parameters of an individual athlete, it is possible to construct personalised neuromusculoskeletal (NMS) models [186, 227, 407, 446, 630, 709]. Moreover, with the continuous acquisition of athlete-specific parameters, personalised dynamic neuromuscular model for real-time feedback and visualisation are possible to develop with deep reinforcement learning (DRL) as done recently by Lee at al. [464]). Same model can be used then to track the longitudinal musculoskeletal changes over a training cycle, that could be indicative of training progression, injury risk or overtraining. Typically, the translation of such models to field use or typical clinical applications is challenging as often the acquisition of all these modalities are not done. There is a desire to either sample the missing modalities from a generative deep learning model [177, 737, 889], or train a deep learning model to approximate a full set of measures, using for example a low-cost wearable sensors such as IMUs [630].

E. Overtraining: Heart Rate Variability (HRV)

Heart rate (HR) monitoring, either via optical photoplethysmography (PPG, e.g. on ring or on smartwatch) or electrocardiocardiographic (ECG) chest straps, are probably the most commonly used wearable sports technology. HR monitors are frequently used in endurance sports monitoring [838], but they have been recently used in strength training to assess the overtraining/recovery status of the athlete [511, 655, 805], often involving overnight sleep recordings rather than during the training session itself [756, 877]. From these measurements, heart rate variability (HRV) is the most commonly derived parameter [193, 389], with the ring or wrist band monitor/sensor offering ease-of-use and good adherence. However, the relatively lower signal quality of PPG compared to ECG chest strap, should be noted [631] as it contributes to higher uncertainty in derived HRV parameters. Early research on using HRV with strength training was promising [129], while the more recent studies suggest caution for the usefulness of HRV use for assessing the recovery status of the athlete [233, 351, 591, 805].

F. Thermal and circadian measurements

It is well documented that there is intramuscular temperature dependency on muscle force generation [67, 147, 194], and the core body temperature (CBT) exhibiting a circadian rhythm with an amplitude approximately 1°C. The CBT is typically highest during the afternoon and lowest in the early morning depending on the intrinsic phase of the individual [34, 439, 542]. Some have even claimed muscle temperature to be probably the most important factor in determining the outcome of exercise performance [234, 649]. However, it is unclear, how much the circadian rhythm *per se*, generated by 'master circadian oscillator' suprachiasmatic nucleus (SCN) [306], in relation to downstream signals such as temperature, drive the time-of-the-day changes in strength [53, 194] and athletic performance in general [495, 644].

Edwards et al. [206] showed that passive heating and increased humidity was not sufficient to increase strength suggesting some that other intrinsic changes within muscles occur during the day. Some animal studies have suggested that passive heating (e.g. sauna) can stimulate muscle hypertrophy [685], and how it could be used as a mimetic for exercise especially in clinical populations. In "circadian free-running" blind people who are not entrained to the environmental light-dark cycle, it was shown that isometric and isokinetic contraction strength performance mirrored the intrinsic circadian phase of these people, further demonstrating the intrinsic circadian drive in strength production [764]. Zhang et al. [914] showed how maintaining a normal circadian rhythm [341], e.g. regular sleep/wake cycle, can be beneficial for stimulating skeletal muscle repair to prevent or alleviate skeletal muscle atrophy (catabolism).

Thus, it is important to have estimates of the individual circadian phase, core body temperature and muscle temperature during exercise, to better understand the intra- and inter-individual variability to exercise [644, 683]. One could even argue that all the measures reviewed in this review exhibit a circadian modulation, even if the circadian modulation would not yet had been explicitly studied and reported. Additionally, the menstrual cycle phase in females modulates body temperature variations differently from the circadian drive [440], further complicating the analysis of female athletes.

Rectal temperature recording is considered gold standard in CBT measurement [542], limiting its use for continuous measurement in active athletic population, thus various alternative methods to measure CBT have been proposed. The use of commercial wearable skin surface thermometers called iButtons® worn on multiple locations on body has probably been the most used alternative for rectal measurements [305]. Measurement with iButtons® traditionally required multiple measurement locations, with recent research devoted on reducing this requirement with development of mathematical modeling [208, 427], even going down to single-site measurements from wrist [521], finger [510], and chest with a wearable patch [652].

These continuous and invisible temperature measurement could be used as real-time proxy measurement of changes in circadian phase [167, 190, 301, 330, 772, 849], i.e. assessing at what hour the individual athlete's performance peaks allowing individualised training times [196, 277, 727], assessing the efficacy of anti-jetlag interventions when having to compete on a different time zone [669], and facilitating general monitoring of stable circadian entrainment to environmental light/dark cycle [205, 475, 691]. Similar to the challenges in CBT measurement, measuring muscle temperature has been traditionally time-consuming and cumbersome, with novel methods such as insulation disk (INDISK) techniques being proposed to make muscle temperature measurement easier while still physiologically valid [92, 234].

The multisite temperature recording with wearable iButtons ® for distal-proximal skin temperature gradient (DPG) measures, and for quantification balance between core and skin temperature [438], can be also approximated optically with non-contact imaging infrared thermography [559]. Imaging infrared thermography have been used in few sports science studies, e.g. for prediction of body part specific injuries [162, 271], as a non-invasive marker for delayed onset muscle soreness (DOMS) [641], and as a measure for activation of motor units in Olympic weightlifting [450].

For sports applications, the recent advances in functional optical fibers [130], could allow smart compressive garments of the future to provide continuous temperature measures for estimation of core body temperature, DPG and intramuscular temperature. Example of such a sensor was developed by Guo et al. [284], who demonstrated a prototype system for real-time measurement of bicep temperature during dumbbell curls. Such a wearable fibre-optic system with non-thermal modalities is demonstrated in Light Lace® smart garment from Organic Robotics (https://www.organicroboticscorp.com/), that integrates measurements of motion capture, muscle activity and respiration into a single garment [894].

G. Brain Imaging

Athlete's focus, fatigue levels, and 'mind-muscle' connection [326, 624] can be monitored in sports application with portable brain imaging techniques such as dry electrode electroencephalography (EEG) [244], or functional near-infrared spectroscopy (fNIRS) [325, 436]. EEG studies have shown how the most fatiguing strength training protocols were associated with greatest increase in cortical activity [232]; how during eccentric contraction, prefrontal cortex seemed to be more involved in the regulation of cortical motor drive compared to isometric and concentric contraction [311]; and how focusing attention on muscle exertion can increase EEG coherence in a cycling task [243]. Recently a magnetic resonance imaging (MRI)-compatible foot pedal device was developed allowing also functional MRI studies for lower extremity movement [192, 281]. Additionally, the mental load quantification from brain imaging might be useful if the weight training with biofeedback is implemented in VR [228, 648], and the mental load could be used to modulate the weight training complexity [263], as done in clinical applications for gait rehabilitation [398].

H. Biochemical biomarkers

In addition to the electronic measurement techniques outlined above, athletes can be monitored for muscle damage and recovery status [135, 618], using numerous biochemical and multi-omics measures [582], sampled from blood, urine or sweat. The sweat-based sampling is the most invisible for the athlete as the developed sensors are typically small [41, 265], around the size of a typical bandage [802]. Lactate and ammonia levels are probably the most interesting for strength training purposes. Lactate levels can be used to track metabolic fatigue and ammonia for assessing neuromuscular fatigue [697]. Additionally, both can be used to track acute recovery between training sets. One of the main remaining challenge in sweat-based sensing has been to ensure the validity between sweat and blood concentrations [255, 668, 910], with recent non-commercial prototypes showing promising results in providing high-quality real-time measures of various biomarkers (including lactate and ammonia) [802, 910]. Imani et al. [353] co-fabricated electrochemical lactate sensor and electrophysiological ECG sensor on the same flexible substrate to be mounted on a skin, demonstrating how multimodal wearable sensing systems are feasible even today, and how even more comprehensive sensor solutions could be fabricated in the future.

Hormonal sampling is relatively common in strength training studies, including hormones such as testosterone, human growth hormone (HGH), cortisol, insulin-like growth hormone (IGF-1), cortisol and 17β-estradiol [437]. Male sex hormone, testosterone [672] is the most frequently used hormone in strength and hypertrophy studies because of its ability to increase muscle mass even in males who do not do resistance training [76]. As a result, its use is considered as doping in professional sports, and therefore banned in competitive sports [886]. Endogenous testosterone exhibit circadian [309], circannual [274] and acute response to heavy training in both men and women [337, 843]. Absolute testosterone levels [681, 682] and acute testosterone response to strength training [484] being lower in females compared to males. The individual circadian profiles (see III F above) in testosterone levels [309], can be used to optimise time-of-the-day for strength training for optimal hypertrophy and strength gains.

Female athletes need to consider their menstrual cycle for training programming [622, 682, 687], among other gender differences [318, 682]. Follicular phase typically allows larger strength gains and more hypertrophy [781, 872], while during luteal phase the recovery times from training can be prolonged [515]. The use of hormonal contraceptives does not seem to affect the strength performance in physically active women [572].

The intradaily variation of testosterone levels highlight the need of continuous measurement technology [165], with no wearable solution available at the moment, and, gold standard being based on blood sampling with liquid chromatography–mass spectrometry (LC–MS) analysis [110, 157]. Preliminary evidence on electrochemical sensors suggest that in near-future, wearable sensing systems could exist for sampling steroid hormones such as cortisol [735, 913], 17β-estradiol [793] and testosterone [13].

Creatine kinase (CK) monitoring has been the most commonly used biomarker for assessing muscle damage and recovery, mostly due to its ease of identification and low cost of assays [425]. Total serum CK activity is typically elevated for 24 h after the exercise, and returns to baseline levels with rest. If the CK levels remain high at rest, a full diagnostic workup should follow for the athlete [93]. The practical problem arises with the definition of "high" CK levels, as total CK levels depend on age, gender, race, muscle mass, hydration level, physical activity, and climatic condition [93]. Additionally, athletes have large inter-individual CK response differences to the same exercise, further complicating the analysis of CK levels for recovery status [93]. Other biomarkers, which can be analysed for exercise recovery include transforming growth factor beta 1 (TGF-β1) [408], oxylipin [744], brain-derived neurotrophic factor (BNDF), oxygen reduction potential (ORP, redox potential) [647], cell-free DNA (cfDNA) [60], and neutrophil phenotypes [762].

In the emerging field of multi-*omics* [9, 131, 918], relatively little research has done on exercise physiology [187, 564, 582]. Knab et al. (2020) [422] showed how proteomic markers from finger-pricked blood sample could be used to predict the athlete stress and athlete-reported illnesses such as upper respiratory tract infection. Kim et al. (2020) [409] suggested that myostatin A55T genotype was associated with quicker strength recovery following exercise-induced muscle damage. The recently formed Molecular Transducers of Physical Activity in Humans Consortium (MoTrPAC) [700] being one of the most ambitious research programs on the use of omics in exercise physiology. MoTrPAC will attempt to better define *omics* responses to chronic exercise training at varying exercise intensity levels and exercise modalities.

In general, athlete monitoring would benefit from continuous noninvasive blood sampling [635], as is the case with other measures reviewed here, to better capture the intra-day and long-term variations both within and across athletes. In the future, low-cost continuous noninvasive blood sampling [635] could be done routinely along with automatic gut microbiome analysis [347, 582, 629] with "smart toilet'-type systems [613].

I. Subjective measures

In addition to reviewed objective measures, there is tremendous values in asking the athletes themselves to rate the quality of their training sessions, recovery status, and general wellbeing. In the systematic review by Saw et al. [708], it was shown that subjective measures such as mood and perceived stress were shown to outperform blood markers and HR when used as stand-alone measures of sports performance. The authors suggested though that the subjective measures should be combined with more objective measures, and one should not rely solely on subjective measures that might have their own issues with bias and data quality [107, 369].

The rating of perceived effort (RPE) on a scale from 1 to 10 [87, 295, 434, 522], and its strength training specific RPE scale *repetitions in reserve* (RIR) [48, 824, 933], which estimates how many repetitions you believe you could have done before reaching a technical failure within a set, are probably the most commonly used subjective measures in strength training. These measures are found in advanced gym logger such as Gravitus® (https://gravitus.com/) [314] or Reactive Training Systems'® web app (https://www.reactivetrainingsystems.com/AppHome). Helms et al. [320] for example showed that RPE was an useful tool for prescribing training intensities for powerlifters, in addition to traditional methods such as percentage of 1RM. Larsen et al. [457] also found the subjective markers, especially when combined with objective velocity markers [123], were useful for strength training programming and monitoring. These findings highlight the necessity of subjective measures in precision strength training frameworks for better understanding of the full biopsychosocial profile of the athlete [160, 809].

However, as all subjective measures, RPE scales have their methodological shortcomings [295], and for example Halperin et al. [295] argued that RPE should be accompanied by other subjective measures of affect, fatigue and discomfort, among other measures. The authors proposed the Feeling Scale (FS) , for affective valence in resistance-trained participants with preliminary for real-word use [295] and warranting more detailed followup studies [213]. However, the use of RIR is limited to advanced elites, as its efficient use depends on the ability of athletes to predict maximum effort and being able to separate the perception of effort from actual effort [767], which has been proven to be challenging to intermediate-level lifters [32].

IV. DATASETS FOR STRENGTH TRAINING

In order to build data-driven precision strength training models, strength training specific datasets need to be acquired first, with relevant modalities and data quality high enough for human movement studies [575, 728]. Currently, no large-scale open-source exercise dataset, or let alone strength training dataset exists (figure 4A), thus we will introduce the concept of *self-supervised learning* and how to use existing datasets and pre-trained models for custom datasets (figure 4B). Finally, a short overview of technical details relevant for custom dataset acquisition is presented in figure 4C).

A. Datasets for exercise and physiotherapy

To the authors' knowledge, no large-scale open-source databases exist for the development of strength training specific deep learning models. Thus we will review here the existing datasets for generic action recognition models, containing sports activities, physical rehabilitation and the small strength training datasets. Kinematic skeleton databases derived from RGB(-D, D for depth channel) video are the most common type of dataset available [915]. The largest and most frequently used datasets for benchmarking datasets for deep learning model development[3] are NTU

[3] https://paperswithcode.com/task/skeleton-based-action-recognition

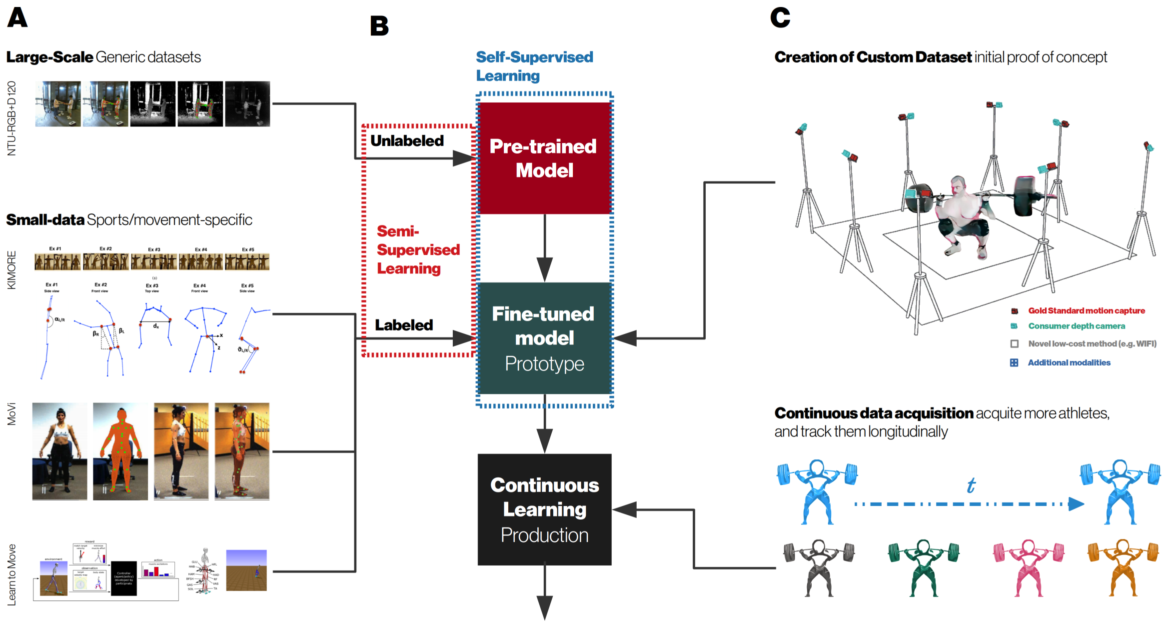

Figure 4. Process of re-purposing available large-scale datasets such as NTU-RGB-D 120 [486] for sports and strength training deep learning development. **(A)** Large-scale action recognition dataset NTU-RGB-D 120 contains skeleton data of everyday activities which can be used as an initial pre-trained model **(B)** using recent self-supervised learning approaches that are shown to learn good generic features [932], to be used for finetuning with smaller domain-specific datasets (e.g. `KIMORE` [111], `MoVi` [267], `Learn to Move` [758]) for your desired task. Semi-supervised learning refers to the 'unlabeled' generic datasets that has no sports-specific labels necessarily that are used to supervise the fine-tuning. Physiotherapy datasets such as `KIMORE` [111] could be used to quickly develop physiotherapy movement assessment models with the self-supervised approach [782], and as no open-source strength training dataset is available, one could capture kinematic data with multiple cameras with different quality levels for example **(C)**. The multiple views reduce the self-occlusion and joint location uncertainty and multiple quality levels allow the simulation of low-quality deployment hardware. After the acquisition of this initial dataset, one wants to continuously acquire new data from more athletes to continuously improve the model and validate the performance of the model.

RGB+D 60 [733, 807], NTU RGB+D 120 [486] and Kinetics-Skeleton [393, 897], all captured with Kinect [14, 148, 626]. The exercise-specific datasets are considerably smaller and are mostly acquired for clinical physiotherapy purposes [477] (see table I), but these datasets could be pooled together as a base dataset for sports specific modeling (figure 4A). It should also be noted that none of the published datasets seem to contain longitudinal recordings for developing athletic training progression models and assessing intra-individual variability.

Capecci et al. [111] published the `KIMORE` dataset recorded with Kinect^{TM} consisting of physical rehabilitation body weight exercises recorded with a total of 78 subjects from five different patient groups: 1) healthy, experienced in exercises; 2) healthy, non-experts; 3) stroke rehabilitation; 4) Parkinson's disease; 5) low back pain. Leightley et al. [469] published quite large dataset `K3Da` containing 54 subjects performing 13 different standardised tests for physiotherapy. `AHA-3D` dataset [24] contains 21 subjects, both young and elderly subjects, performing body weight exercises. Parisi et al. [606] collected a dataset consisting of 17 volunteers performing high bar back squats, deadlifts and dumbbell lateral raises, but the dataset was not made public. Cuellar et al. [170] published physical therapy diagnosis exercises with 10 subjects acquired with Kinect. University of Idaho – Physical Rehabilitation Movements Data Set (`UI-PRMD`) [834] consists of 10 healthy subjects performing rehabilitation exercises such as deep squat, hurdle step and sit to stand captured both with Kinect^{TM} V2 and Vicon^{TM} Optical tracking system. Home-based Physical Therapy Exercises (`HPTED`) consist of only 5 subjects performing shoulder and knee exercises [25]. Militaru et al. [549] collected a dataset small 2,400 image Kaia^{TM} -style [815] dataset to train a form correction network for plank and holding squat.

For accelerometer-based data, Ebert et al. [203] published a dataset consisting of 8 different body weight exercise with 26 subjects encompassing more than 11,000 exercise repetitions in total, and Taylor et al. [797] published dataset with 3 gym exercises using 9 knee osteoarthritis patients. Reiss and Stricker [665] recorded HR with IMU data for 9 subjects performing physical activities. Kwon et al. [451] addressed the lack of modality-specific training data with their `IMUTube` system that can convert YouTube videos of human activity into vir-

Table I. Datasets published for body weight physiotherapy exercises, and gym-based exercises with weights.

Dataset	Year	Modalities	Exercise types	n	Exercises	Multi-modal	Available	Ref
	2006	EMG	Squat	9	3	–	–	[584]
	2010	Accelerometer	Gym exercises	9	3	–	–	[797]
`PAMAP`	2012	IMU, HR	Everyday activities	9	18	–	✓	[665]
`HPTED`	2014	Kinect®	Physiotherapy	5	8	–	✓	[25]
`PReSenS`	2015	Kinect®	Physiotherapy	10	2	–	–	[170]
	2015	Kinect®	Gym exercises, incl squat and deadlift	17	3	–	–	[606]
`K3Da`	2015	Kinect®	Physiotherapy	54	13	–	✓	[469]
`EmoPain`	2016	Face videos, Kinect®, EMG	Physiotherapy	50	11	✓	✓	[37, 207]
	2017	IMU	Body weight gym exercises	26	8	–	✓	[203]
`MyoGym`	2017	EMG	Gym exercises	10	30	–	✓	[431]
`UI-PRMD`	2018	Kinect®, Vicon®	Physiotherapy	10		–	✓	[834]
`AHA-3D`	2018	Kinect®	Physiotherapy	21	4	–	✓	[24]
`KIMORE`	2019	Kinect®	Physiotherapy	78	5	–	✓	[111]
`PennAction` subset	2019	RGB video	Squat	?	1	–	✓	[845]
	2020	Smartphone	Physiotherapy	?	2	–	–	[549]
`MoVi`	2020	IMU, Qualisys®, smartphone, industrial camera	Everyday activities	90	21	✓	✓	[267]
`EV-Action`	2020	Kinect®, Vicon®, EMG	Everyday activities	70		✓	✓	[856]
`MM-Fit`	2020	RGB-D video, Smartphone IMU, smartwatch, earbud	Gym exercises	10	10	✓	✓	[774]
	2020	Raptor-E® mocap	Movement screens	417	21	✓	–	[91, 149]

EMG electromyography, IMU inertial measurement unit. Kinect® is an example of low-cost motion capture system, and Vicon®/Qualisys®/Raptor-E® of 'gold standard' level motion capture.

tual streams of IMU data, i.e. synthetic kinematic training data that you could acquire from strength training videos available in abundance.

Ghorbani et al. [267] published an interesting multimodal dataset `MoVi` that contained both IMU and kinematic data of sports movements from a total of 90 subjects, 60 females and 30 males. Koskimäki et al. [431] published `MyoGym` dataset containing 10 people doing 30 different gym exercise wearing the sEMG Myo™ armband [431]. Wang et al. [856] combined kinematic data from Vicon™ and Kinect™ V2 with electromyography (EMG) for their `EV-Action` dataset and recorded 70 subjects performing various actions, not all sports specific. Vyas [845] had used 391 squatting images from `PennAction` [917] to train an action recognition model for detecting squat exercise. Stömbäck et al. [774] introduced `MM-Fit` dataset, which was collected using IMUs on smartphones, smartwatches and earbuds worn during gym exercises.

The use of movement screens [441] (e.g. Functional Movement Screen, FMS™, Functional Movement Systems, USA) has been increasing, especially in sports talent identification in major US sports leagues such as NBA™, NFL™, NHL™ and MLB™, often with very subjective assessment [530]. Recently, more quantitative and objective athlete approaches have emerged for whole-body movement phenotyping [470, 666, 688]. Clouthier et al. [91, 149] studied a proprietary dataset acquired from 417 athletes, each performing movement tests consisting of 21 unique movements. The authors showed how deep learning seems promising in automating the assessment of movement screens. These types of movement screen datasets, if made public, would be very valuable for sports, physiotherapy and ergonomics assessments.

For musculoskeletal modeling purposes, "Grand Challenge to Predict In Vivo Knee Loads" [239, 412] and "Comprehensive Assessment of the Musculoskeletal System" (`CAMS-Knee`) [798] provide very specialised datasets for modeling knee contact forces (KCFs) using ground reaction forces, kinematics, EMG, computed tomography (CT), and stationary fluoroscopy data. Imani Nejad et al. [354] studied the difference between `OpenSim` model predictions and actual measurements from `CAMS-Knee`, and highlighted the subject-specific variability in musculoskeletal predictions. The dataset of "Learn to Move" competition[4] is not directly on sports movement. However, the task is to develop a deep reinforcement learning controller for 3D human musculoskeletal model, which could be extended to sports and clinical use in the future [758].

B. Finetuning existing datasets for strength training

In deep learning it is a common practice to take a pre-trained model, initially trained on a large-scale generic dataset such as ImageNet [96, 185, 779, 908], which contain natural images of different dog breeds and flowers. Then, the pre-trained model is repurposed to a custom task with only little data available via *fine-tuning* (also referred as transfer learning) [38, 137, 570]. Previously the preferred ways for fine-tuning models have been either pre-training the model from scratch using unsupervised learning and then freezing some of the network layers and continuing model training with supervision from your own dataset labels [904], or taking the pre-trained model and freezing all layers but the last layer [264, 512].

Recently, these approaches have been replaced by fine-tuning with self-supervised learning (figure 4B) [38, 134, 278, 370, 424, 791, 921, 932]. In practice self-supervised learning is between unsupervised learning, in the sense that humans do not need to annotate anything, but the learning is supervised with automatically created supervision labels. For example in Bootstrap Your Own Latent (`BYOL`) approach [278], the supervision targets are synthetically augmented (algoritmically distorted) versions of the input data [65], allowing the network to learn representative features from the large-scale dataset.

Spathis et al. [760] used HR as the (self-)supervisory signal for activity data, to learn human activity recognition (HAR), and demonstrated first multimodal self-supervised approach for lifestyle monitoring outperforming unsupervised autoencoders [695]. For pose estimation and future pose prediction, Suris et al. [782] pre-trained first the model on larger `Kinetics` dataset [393], and then fine-tuned the model on a smaller `FineGym` dataset [734]. They showed how smaller movement dataset can benefit from an initial self-supervised pre-training first on a larger dataset [932]. This type of training involving both task-specific (labelled) and generic (unlabelled) data, is referred as semi-supervised training [214, 731, 794].

[4] NeurIPS 2019: Learn to Move - Walk Around https://github.com/stanfordnmbl/osim-rl

C. Creating your own custom dataset

With the lack of strength training specific datasets, even the development of proof of concept precision strength training model will require for the sports scientists to acquire a novel custom dataset. Proof-of-concept powerlifting dataset could contain longitudinal trend over a mesocycle (e.g. 4 weeks with 3 weeks of progression, and 1 week of *deloading*); intra-individual variation during one set, one exercise, one session; and inter-individual variation between athletes for the same exercise prescription in order to capture the information related for the sport in question [876].

The exact technical measurement setup depends on the project resources, but could contain at least kinematic, kinetic, activation and morphological characteristics (III) giving a more complete view of the athlete's training progress (i.e. multimodal model [145, 858]). The multimodal dataset would also allow the use of classic musculoskeletal modelling techniques [227, 407, 465, 630, 709], and more recent deep reinforcement learning musculoskeletal models [758] for strength training purposes (figure 4C). With all the modalities recorded, it is then possible to simulate measurement conditions when not all the modalities are available. This would give an opportunity to demonstrate the relative importance of different modalities [146, 657], how missing data could be generated or handled [289, 290, 331], and how these affects your model's performance. One could additionally include multiple devices of the same modality at various quality levels [384, 448, 759, 783, 920], enabling the quantification of data quality to model performance, e.g. replacing a high-end motion capture system such as Optitrack/Vicon [817] with a Kinect or a smartphone to evaluate how it would affect the model performance [14, 540].

Attention should be paid into optimising the quality and ease of use of the data annotation pipeline [150, 346], e.g. the spatiotemporal quality of joint locations [575, 728] or temporal segmentation of individual repetitions and during exercises [75, 183, 360, 688, 774, 833, 857]. In sports laboratory conditions, the uncertainty of body pose estimation uncertainty could be mitigated by the use of extra infrared retroreflective straps as fiducial markers [128, 156, 230, 405], while the general trend however has been towards markerless motion capture systems [120, 256, 575, 739]. In practice, the use of additional markers is cumbersome for the athlete, and can even increase measurement uncertainty with Kinect™ [573, 786]. Colombel et al. [153] recommended the use of miniature markers with a diameter of 2.5 mm to reduce the interference with Kinect™ Azure.

It should also be noted that, Kinect™ v2 encodes the spine in the skeleton with just 3 joints [870], which might limit the assessment of lumbar–

pelvic movements (LPM), e.g. the "butt wink" in powerlifting jargon during squat that may load specifically L5-S1 joint [204]. LPM analysis is of a particular interest with low back pain patients [702, 822]. The assessment technology for low back pain, such as recently proposed low-cost electronic skin sensors [919], could be used in strength training and physiotherapy research. [22].

In Kinect™-based systems it is common to use multiple devices simultaneously to capture the athlete from multiple angles (multiview capture) to reduce self-occlusion and joint location uncertainty [14, 184, 372, 710, 770, 816]. However, in practice the system often would like to be deployed to field with just a single Kinect or a smartphone camera [746, 775]. Depending on the application, the single Kinect™ might not be provide sufficient joint angle resolution, with Colombel et al. [153] demonstrated the side placement of Kinect™ Azure devices to giving better signal fidelity over front-facing device. As an example from hand tracking research for VR, Han et al. [300] used 16 separate cameras to obtain the highest hand joint location ground truth. High quality dataset acquisition, with multiple views, modalities and data quality levels, might also help with designing better data augmentation techniques [124, 182, 449, 491, 703], pre-trained networks [853], and defence for adversarial attacks [609], to further improve deep learning performance with small datasets.

1. *Continuous learning*

The researchers should be prepared for the continuous data acquisition, i.e. the iterative improvement of the trained model. In hospitals where the new data is continuously acquired "for free" from patients, but the labelling/annotation of the data by human experts is expensive, *active learning* systems are frequently used [223, 417, 490]. These systems attempt to predict the most useful (i.e. not a typical patient already found within a labelled dataset) unlabeled data to be labelled by humans for maximising model performance [98, 200, 553]. In strength training, analogous situation could occur when routinely only the kinematic data of every monitored athlete in a given training centre is being recorded, and in the occurrence of any anomalous movement patterns would be tested (compared to existing dataset, i.e. exhibiting high *epistemic* uncertainty [266, 366]), other modalities such as kinetic, activation, and morphological parameter would also expect to be anomalous and therefore, valuable to be included to the labelled dataset to increase the generalisation capability of the model [201, 506].

When one disseminates the knowledge from the updated model to practice, and from practice back to modeling, these systems are referred to as "learning health systems' [533, 585]. Similarly one could hope that in the future, *learning precision strength training systems* would be introduces, in which the developed strength training models would influence strength training practice in the field, and the training practice would influence the work of model development for strength training [865].

Lifelong, or continual learning is a concept often used in autonomous robotics, in which the robot is able to fine-tune its own performance continually through its experience [291, 608, 837]. In physical rehabilitation and in athletic training such a situation could occur with a robotic coach learning the correct movement from physiotherapist via imitation [3, 518], and eventually becoming an autonomous robotic physiotherapist or personal trainer [660], able to help in at-home exercise. Such robotic systems could be pooled together in a *federated learning* framework, where the training would be decentralised [676, 706, 895, 899, 903], and the individual robots would be considered as "smart edge devices' [552, 800]. Conceptually, this type of distributed system would allow, the heterogeneous coaching style to be pooled into the same model, without the coaches or sports teams/institutes having to give ownership of the data to a model aggregator [823]. The model aggregator, could then be the device manufacturer providing the technology for athlete tracking, or athlete management system (AMS) provider as attempted by Google DeepMind with their Streams EHR for clinical care [638].

The third, similarly sounding concept to the previous ones, is *continuous delivery*, that refers to software engineering practices to foster automation and, quality and discipline to create workflow for deploying software into production [178, 723, 925]. Often academic studies, are mostly interested in developing new proof-of-concept models, with little thought on real-life software translation and the engineering modules needed for deploying these to "production' [725]. The field focused on improving these deployment practices is referred as *MLOps*, aiming to unify machine learning (ML) system development (ML + Dev) and ML systems operations (Ops). The concept of MLOps is derived from *DevOps* that is commonly used software engineering practice making software production and deployment automated and repeatable. What sets MLOps apart from DevOps, is how data and code is managed jointly, as new data can change the behaviour of the system (Software 2.0 [553, 869]), whereas in contrast to DevOps in which the program code defines solely the function of the system [251].

V. DEEP LEARNING ENABLED EXERCISE AND STRENGTH TRAINING

The majority of deep learning studies and startups have targeted recreational gym-goers [145, 850]. For example, algorithms and models have been developed for exercise recognition [401, 587, 646, 651, 747], automatic training diary logging [359, 403, 774], repetition counting [27, 639], adherence monitoring [103], and real-time exercise technique evaluation and correction [117, 133, 254, 349, 371, 372, 589, 607, 610, 845, 900]. The technique assessment models (or motion similarity models [726, 835]), are the most relevant from these models for our precision strength training assessment for kinematic assessment of the athlete. Notable weight training startups [312] include for example Tonal™ (https://www.tonal.com/), Tempo™ (https://tempo.fit/), and Keep™ (https://www.keepkeep.com/).

Tonal's digital weight system with programmable resistance over the single movement itself [191, 410, 414] is the most interesting of these for precision strength training purposes. One could replace the use of physical chains [583, 846] and elastic bands [19, 202, 381, 447, 516, 662] with digital programming of load changes during one repetition for improving the athlete's lift "sticking points' [429]. Additionally, given an accurate enough individualised neuromuscular model, one could detect fatigue over the training session and dynamically adjust the load for the athlete, e.g., when the training is programmed with RPE [321, 443, 457] (see III I) or velocity loss targets [861, 862] (see V A 1). This type of a real-time adaptive system could be used as an input for gamified exergames such as *StrengthGaming* [453], for the clinical rehabilitation and general population to make the training more fun, especially for individuals with adherence issues.

A. Powerlifting: example sports for precision strength training

Algorithmic approaches specifically for elite-level S&C, and competitive strength sports are more scarce than for recreational use (see for example JuggernautAI™ in section §I). Strength sports involve sports as powerlifting [670], Olympic weightlifting [759], bodybuilding [17], CrossFit™[520], strongman competitions [334], arm wrestling and grip sports. Powerlifting seems the most suitable sports from these to illustrate the concept of *precision strength training* in practice.

In powerlifting [225, 320, 821], the goal is to produce maximum force, in a relatively long time window [829], in the three powerlifting lifts: squat [154, 390], bench press [605, 876] and deadlift [217, 390]. The effect of lifting technique *per se* to the amount of load lifted is smaller in powerlifting compared to the effect of lifting technique in Olympic weightlifting [670]. This simplifying the performance monitoring, as the lifted weights reflect more closely the strength performance with less effect from variations in lifting technique. In Olympic Weightlifting, the rate of force development (RFD) is higher than in powerlifting [829, 911], i.e. how explosively the movement is executed, in practice also requiring faster motion cameras than powerlifting. Bodybuilding aims to maximise muscle mass (hypertrophy) with less focus on strength performance [17, 555], and the quantification of muscle mass changes is less straight-forward [308]. Hypertrophy studies would require muscle biopsies and more advanced imaging techniques to properly quantify the progression of the athlete [1, 505].

Additionally, powerlifting lift variants are very commonly used by recreational gym-goers and S&C coaches for non-strength sports, making the analysis of powerlifting generalise well to multiple sports. However it should be noted, that not all sports necessarily benefit from powerlifting-type of strength training, i.e. the strength gains do not necessarily transfer to improvements in sports performance [532, 778, 905, 906]. For example, sports requiring explosive power such as boxing [498, 765], taekwondo [485], track and field sprinting [307, 500], and mixed martial arts (MMA) [317, 367, 416, 433, 472, 888], often benefit more from ballistic/plyometric training with a goal to improve athlete's explosive strength capability [829].

Sjöberg et al. [748] conducted an interesting study, with a group of 3 national level Swedish powerlifters, who compiled list of lifting technique issues in squat and deadlift, with relevance for the risk of injury. This list was then evaluated by 14 domain experts consisting of coaches, researchers and competitors within International Powerlifting Federation (IPF), resulting in a new protocol for evaluation of lifting technique. This could be interpreted as the first step of establishing and evidence-based recommendations regarding safe technique in the powerlifting squat and deadlift, and as a qualitative human expert basis to train deep learning networks on movement assessment. The level of inter-rater disagreement and "collective intelligence" [650] between the 14 domain experts furthermore would allow the quantification of uncertainty in lifting assessment, a probabilistic aspect typically desired in deep learning for safety-critical applications such as healthcare [77, 366, 382, 428, 659, 792].

In powerlifting, it is well known qualitatively that body dimensions affect lifting techniques, i.e. how the anthropometric properties of the athlete will affect the definition of 'correct form' [142, 226, 603, 839, 842]. This obviously complic-

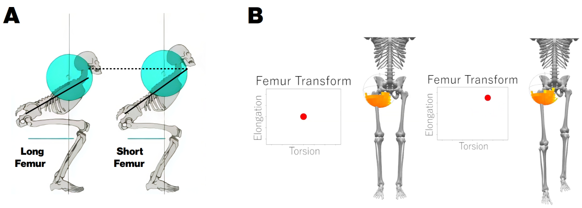

Figure 5. The definition of "gold standard' movement execution is complicated by anthropometric variability in athletes. (A) The athlete with shorter femur compared to trunk, can squat more upright, more easily deeper, and closer to the "textbook standard" of a good squat, whereas the athlete with long femurs has more forward tilting and more cantilever. The athlete with long femurs can try to make the squat deeper for example by placing a block under the heels or using a wider foot stance. In practice, an automatic analysis of squat technique is further complicated by differences in ROM, ankle/hip mobility and tendon/muscle stiffness that we would like to capture for continuously. (B) In computational models such as in the one developed by Ryu et al. [693], it is in theory possible to distinguish these factors, and potentially use it as a framework for athlete monitoring for more fine-grained analysis of technique issues.

ates the development of deep learning models for real-time and offline movement analysis of lifting technique, and increases the data volume requirements (effect size, see e.g. [720, 751] for effect size approximations in deep learning) to capture the inter-individual differences. Anthropometric dependence in Olympic weightlifters was also demonstrated with kinematic data, with the lifters succeeding in competitions with very heterogeneous lifting techniques [171]. In addition to static measures such as trunk/thigh length ratio [246] (5), it might be useful to quantify measures such as ROM [636], tendon stiffness [270], and ankle mobility [246] dynamically in real-time to better understand the dynamic changes during one session and over multiple sessions in movement technique. Additionally, one need to consider the age of the athlete, as deep squat hip kinematics in young athletic adults seem to differ substantially from older and non-athletic subjects [342].

To the knowledge of the authors, no quantitative frameworks have been developed to address the issues of anthropometric variability in lifters for exercise analysis, beyond the suggestion of Cholewa et al. [142] for athletes with greater torso to total length ratios to favour sumo-style deadlifts over conventional style. In practice, the inherent ambiguity in definition of correct form could be modelled for example with deep reinforcement learning (DRL), which have been used medical modeling problems when the exact ground truth is unknown and/or hard to estimate [576, 640, 855]. The developed video-based automatic kinematic assessment could be also used by powerlifting organizations such as IPF to quantify squat depth in real-time, and possibly automating squat depth assessment and reduce subjective judging bias from powerlifiting meets (competitions in powerlifting jargon) [108, 546, 596]. Additionally, the same computer vision techniques could be used in making powerlifting or strongman competitions more spectator-friendly sport with improved sports visualisation [84, 656].

1. *Velocity-based training (VBT)*

Recently, velocity-based training (VBT) and the commercial products related to it have become increasingly popular. VBT is a contemporary method for prescribing strength training based on load/force-velocity curves [481, 557, 861]. One possible application of VBT in training monitoring (see section §II), is to record the velocity of the barbell at different loads (e.g. 45-55-65-75-85% of 1RM [623]), and use load-velocity curve for the estimation of 1RM [116, 623] (figure 6), without the athletes having to actually lift the 1RM, which would be often counterproductive and increase risk of injury. Mean concentric velocity (MCV) is the most commonly used metric in VBT. As demonstrated by Williams et al. [876] the changes in MCV seem to be more sensitive indicator of neuromuscular fatigue compared to measures of maximal strength production. In other words, the use of VBT could potentially be used to track the internal load of the athlete (see section §II), rather than tracking repetitions done at specific loads over the training cycle.

The research interest in VBT has been reflected in the amount of companies offering solutions based on custom camera systems, smartphone cameras, linear transducers or IMUs to measure the velocity of execution. Camera systems are offered by companies such as Perch^{TM} (https://perch.fit/) and GymAware^{TM} (https://gymaware.com/) [594, 860]; IMU systems by PUSH^{TM} band (https://www.trainwithpush.com/) [122, 138]; and smartphone applications by My Lift^{TM} [47, 519], iLOAD^{TM} [694], PowerLift^{TM} [46] and Iron Path^{TM} (http://www.theironpath.com/) [391]; and open-source approaches by Kinovea (https://www.kinovea.org/) [373] and Open Barbell (http://squatsandscience.com/) [272] from RepOne Strength^{TM} (https://reponestrength.com/). One should pay attention on the possible conflict of interests in the validation studies. For example My Lift^{TM} app was validated by the app developer himself [47], and external validation study advised against the use of My Lift^{TM} for VBT [519] due to its excessive velocity errors. In summary, camera-based systems tend to produce more accurate velocity estimates [519, 623], and currently they are preferred over IMU systems.

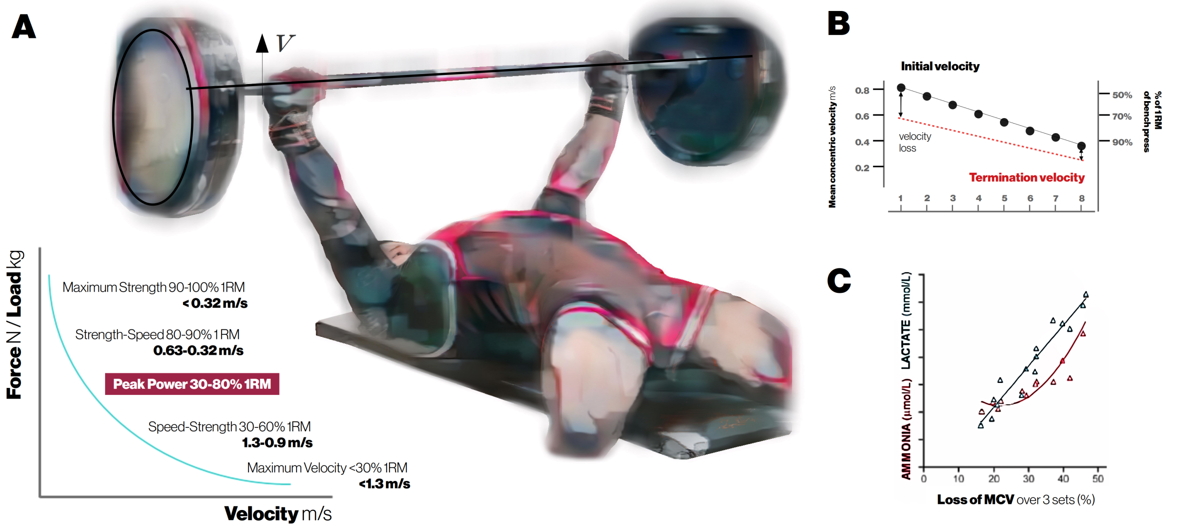

Figure 6. Velocity-based training (VBT) (A) Given a camera or an IMU-based system, one can use the execution velocity (e.g. velocity of the barbell in bench press [273, 698]) to program the training. Bench press velocities across RM range. (B) Example of an 8-week program from Weakley et al. [860] with velocity loss targets for each week, i.e. providing an alternative quantitative target to % of 1RM, to achieve and not go further on each training session. (C) With real-time sweat-based sensing, one could track metabolic (lactate) and neuromuscular (ammonia) fatigue to estimate optimal inter-set recovery [697]. Figure modified from Wikipedia, licensed under CC BY 2.0 (https://sv.m.wikipedia.org/wiki/Fil:Bench_press_yellow.jpg).
1RM 1-repetition maximum, MCV mean concentric velocity

VI. VISUALISATION, SERIOUS GAMES AND REAL-TIME FEEDBACK

For both real-time and offline analysis, it is not trivial how the visualisation of an individual training session, and progression over training cycles is implemented. The subtle changes in movement and the associated physiological parameters during one set or the whole training session need to be visualised [69, 121, 487], and made interpretable to human [164, 336], for effective decision making. Conceptually, one could think of extending the video motion magnification techniques from inter-frame difference visualisation [590], to inter-repetition/set/session difference visualisations.

For example, Baptista et al. [51] used colour coding for each body segment to visualise the correctness of the movement execution. Adithya et al. [45] rendered the athlete as an 3D avatar [426], and visualised subtle motion as swing trajectories and twisting motion with color coding (See figure 7A). For general population, and in clinical applications, an interesting outside-the-box visualisation technique is to involve participants in 3D printing of their activity data (e.g. as food items and allowing better engagement with the exercise or rehabilitation process in a novel and entertaining way as demonstrated by Khot et al. [402] with the *Shelfie* framework.

Lee et al. [464][5] developed a system with the 3D avatar being driven by the output of musculoskeletal model (see III D), i.e. the human motion was driven by the muscle contraction dynamics. The authors demonstrated their model with an avatar doing deadlifts with various loads demonstrating realistic weight-dependent deadlift execution. Additionally, the model allowed the modeling of the effects of pathological muscle weakness and the use of prostheses on biomechanics. In other words, it would be possibly to use the model by Lee et al. [464] with the continuously acquired measures reviewed in section §III as inputs for an athlete-specific musculoskeletal model. The model could be applied in real-time to quantify and visualise sufficient ankle and hip mobility before starting heavy squat exercise and the associated muscle stiffness. As a result, the model could predict suggestions such as an increase in pre-workout warmup or to do a lighter exercise to poor preparedness to train. . Facebook has demonstrated a similar full body tracking model for VR applications with muscle activation simulation along with the kinematic data [6].

The avatar representation, using common game engines such as Unity [746, 757, 927] or Unreal Engine (UE) [12, 29, 83, 488], transfers also well for home based physical rehabilitation and remote athletic coaching through robotic coach. The robot [35, 689], either a physical robot or an avatar,

[5] https://youtu.be/a3jfyJ9JVeM

[6] Facebook 2020 Research: Photorealistic Avatars & Full Body Tracking https://youtu.be/Q-gse_hFkJM(

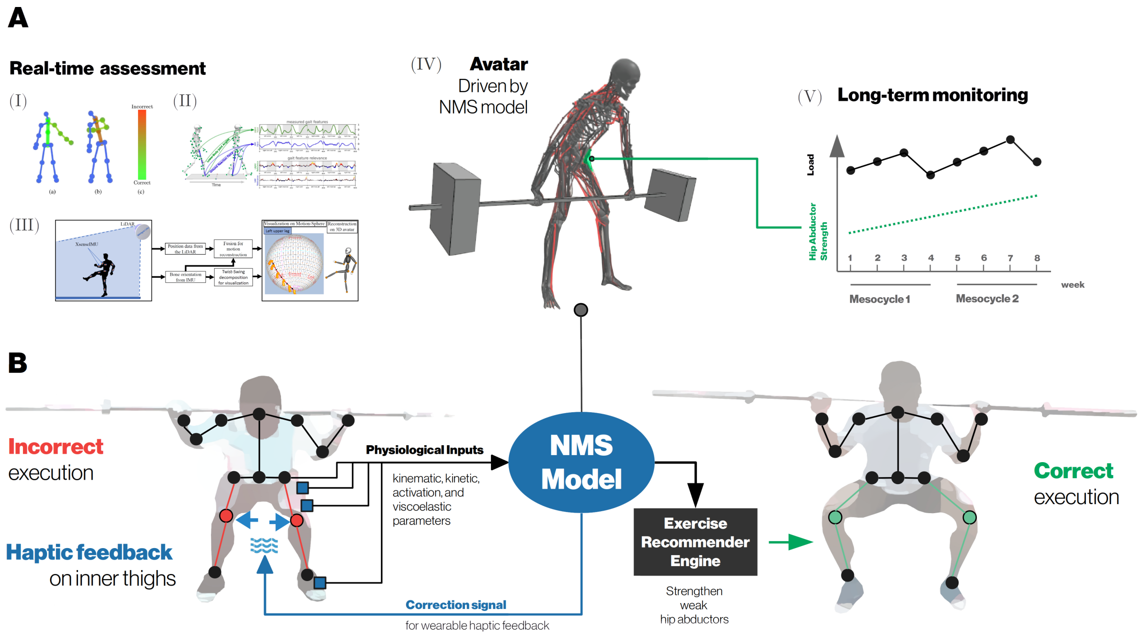

Figure 7. **(A)** Visualisation for real-time motion (I [51], III [45]) and EMG/GRF (II [6, 339]) assessment, individualised neuromuscular model (NMS) driving 3D avatar. The NMS allows specific muscle groups and its effect to movement to be highlighted (IV [464]). In our simplified example, the athlete has a knee valgus [338], resulting from weak hip abductors, and we can follow longitudinally (V, see e.g. [254, 461]) the efficacy of recommended exercises for strengthening. **(B)** The NMS model can be used to drive haptic feedback system, implemented for example in a smart compressive garment, and use to provide real-time haptic feedback for the athlete to correct movement execution. In our example case of knee valgus, the athlete might need a targeted strength training program for strengthening the hip abductors (i.e. gluteus medius, gluteus minimus, and tensor fasciae latae) [158] to mitigate knee valgus. The exercise recommender engine (see e.g. [70, 508, 581, 922]), with the NMS in idealised case would be able to detect automatically overall weakness in hip abductors, or session-specific issues for example due to poor warm-up or insufficient recovery from previous session possibly leading to increased injury risk, complimentary to human expert assessment [316]. The same model could be then used to visualize the progression in hip abductor strength from acquired data, and display it on a dashboard system for the athlete and the coach [254]. Squat images from John Paul Cauchi's video on mitigating knee valgus https://youtu.be/Lt6OxhEHavQ.

can be trained to learn the physiotherapist's or coach's technique suggestions for that given athlete, and becoming able to autonomously interact with the athlete without human intervention [518]. In addition or as alternative way to improve training annotation, one could record the eye gaze of the supervising coach when observing the movement execution, and input the gaze heatmap as an attention mechanism to the model as a supervision for the robot model training [388, 468]. It could be hypothesised that the gaze of the human expert would be focused on the body parts with technique errors, allowing the deep learning to focus more on those video/joint regions during model training for better performing motion quality assessment model.

A. Serious games

Recently, physical rehabilitation programs has been increasingly deployed as *serious games* [86], i.e. the game having utility (seriousness) beyond just entertainment [114]. These have been shown the potential to improve patient adherence to rehabilitation [7, 30], and have been evaluated through randomised clinical trials (RCTs) [86], and validated for improved clinical outcome measures [524]. Serious games have been well received by the clinicians, especially when co-designed with them [31, 54, 72, 459, 884, 887].

Various *exergames*, i.e. games with a fitness aspect, have been introduced as games for the general population [88, 222, 292, 426, 453, 476, 567, 648, 768, 859]. The use of gamification and VR have garnered interest also from elite-level sports [10, 198, 420, 578], but in contrast to physiotherapy, the goal in elite-level sports is often not to improve adherence to training, but to provide complimentary training to real life exercises [787], facilitate sports psychology counselling [80], or to provide preventive mental health care [11, 238, 534, 848]. Ijaz et al. [352] for example showed that VR exergame players can be roughly classified into those that are entertainment-focused (consumers, clinical populations), and those who are exercise-focused (e.g. elite athletes), in practice suggesting that the design of games for such too distinct populations might require very different approaches.

In strength training (e.g. in powerlifting training), gamification of heavy squats in virtual reality is not necessarily desired, so for what could VR be used in strength training? Based on practical experience, a fraction of strength athletes do not like to do sufficiently activities supporting recovery from training such as stretching and mobility exercises. Some athletes find these activities boring and have poor adherence to these activities, and could benefit from making them more engaging and fun to do routinely. One could try to gamify such activities with short term goals, for example with visualising the progress in hip and ankle mobility, and the resulting improved squat 1-RM within a causal model. This game could be further designed to include human expert oversight to avoid injuries [871].

B. Real-time feedback methods

As with visualisation, it is important for the user experience (UX), how the movement quality and the related corrections are communicated in real-time, or offline to the athlete [400] or to the rehabilitation patient [95] after the exercise . The optimal feedback depends on the exercise type, the required mental focus, experience level of the athlete, and the granularity of needed feedback. For example, post-surgery physical rehabilitation patients or beginner yoga practitioners, might be happy with a simple "lower your arms'-type of verbal feedback [602, 661], while others might find it strenuous and needlessly ambiguous [282]. Correctly executed exercise could be rewarded with a simpler auditory feedback such as a click [215], or by a movement sonification such as experimented in physical rehabiliation [579, 711], or with music feedback that was shown recently to improve deadlift technique [499]. In sEMG studies, it was shown tha tfocused verbal feedback had a positive impact on activating triceps brachii more than without feedback [249, 604], highlighting the need of some human oversight and encouragement [565, 852].

Haptic feedback is relatively easy to implement integrated to athletic gear for example as smart insoles [118, 212, 368], embedded in smart compressive garment [235, 598] (see figure 7B), in generic clothing [418, 928], or attached around limbs [827, 929]. In gym environments, providing easily digestible visual feedback becomes challenging as the use of large displays cannot be used for better readability, and the UX with a small smartphone or tablet display, as used by the Perch VBT camera system (https://perch.fit/), can be poor during exercise. Visual and haptic feedback in theory allow body part specific feedback in contrast to binary correct vs. incorrect audio click, in which the degree of correctness is hard to communicate also.

Winchester et al. demonstrated how bar path visualisation and verbal feedback was able to improve kinematic and kinetic performance in Olympic weightlifting, both in clean and jerk [879] and in snatch[880]. Elvitigala et al. [212] showed how it is possible to effectively communicate athlete's centre of pressure changes during squat and deadlifts via haptic insoles and visual aids. Turmo Vidal et al. [827] followed a Research through Design approach [259], and evaluated several feedback methods for gym exercises. The authors found athlete-mounted laser light projection to be useful in monitoring planking posture [828], haptic hip feedback useful for monitoring hip tilt in squat, and arm-worn LED light, similar to the earlier 'wearable displays' [260], to be useful for tracking execution speed of barbell curls. They also highlighted the problems of visual feedback for example with squats, where one does not want athletes to make any undesired head movements and gaze changes, that would increase their risk of injury.

The visual feedback has been shown to work well with less intense exercise such as performing Tai Chi exercises at home [806]. Displaying the video of the user next to the instructor with user skeleton overlaid on the user video, was found to be the most effective feedback for skills learning. With the emergence of so-called "smart mirror systems' [57, 74, 335, 551, 611], it might be possible to overlay all the relevant feedback on the large-scale mirrors typically found in gym and dance studio environments, that most of the athletes probably will find the most intuitive way of receiving visual feedback as they are accustomed already monitoring their execution from mirrors.

VII. CONCLUSION

We have outlined the emerging framework of data-driven precision strength training, adopting the data-driven *precision* from precision medicine, and building on the top of evidence-based personalised strength training to model the intra- and inter-individual variabilities in response to training (see section §II). In practice, despite the recent advances in athlete monitoring technology, long history of data use in sports analytics [531, 536, 550, 714, 882], and the rise of deep learning, no training system yet exists meeting the expectations of precision medicine as translated to strength training [873]. Some companies are riding the "AI hype train' claiming to have be built AI systems on "world's largest datasets" without any external validation for their claims. This is however not a problem unique for "sports AI' though, with many

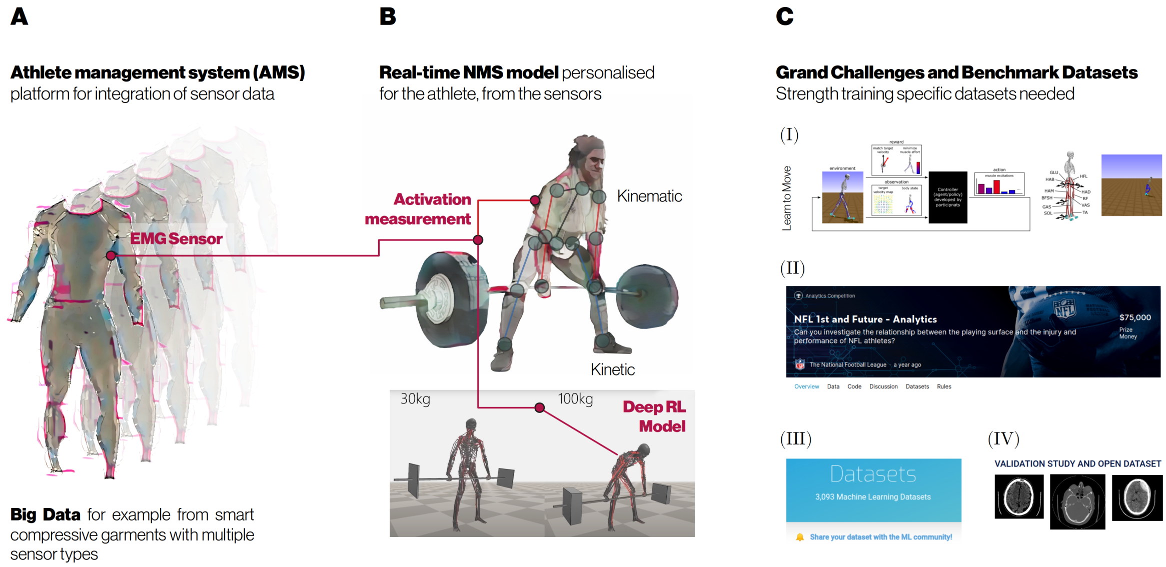

Figure 8. (A) A ubiquitous measurement technology (multimodal sensing) embedded on a smart compressive garment [628]. The new hardware products themselves are not sufficient for precision strength training as exemplified by many failed wearable sensor suits such as Enflux ™ and OMSignal™ [155]. The hardware require data ingestion pipeline that is easily integrated to larger systems such as athlete management systems (AMS) via APIs. (B) The data from compressive garment would then be used to drive the personalised neuromuscular (NMS) model based on deep reinforcement learning (RL) (see figure 7). That could be used to analyse single training sessions and track the progress of the athlete combining all the measurements of the athlete, e.g. the electrical medical records (EMR) and other self-tracked information. (C) Motivating examples on how to open-source proprietary S&C datasets for modelling purposes. (I) Learn to Move challenge is targeted for the deep reinforcement learning community, as a shared benchmark to evaluate different modelling ideas, (II) Kaggle competitions (https://www.kaggle.com/) often come with prize money from sponsors, such as in the NFL™ 1st and Future to predict injuries (https://www.kaggle.com/c/nfl-playing-surface-analytics), (III) Papers With Code | Machine Learning Datasets provide a centralised database for existing datasets and the published models and their performance on those datasets (https://www.paperswithcode.com/datasets), (IV) Qure.ai (https://qure.ai/) is a radiology startup that open-sourced a small subset of their proprietary data essentially as a marketing for their commercial main product [140].

"disruptive" AI-driven companies taking similar marketing-heavy paths [218, 283, 545, 730].

Main challenge facing the development of precision strength training is the lack of suitable open-source and proprietary datasets (see figure 8C). Strength training is waiting for its "*fitbitisation*", i.e. easy to use measurement device with large-scale adoption, for capturing data at elite, *prosumer* and recreational levels, at a data quality level pertinent for strength training individualisation. The sheer amount of data tends to be more valuable in medical deep learning, instead of an over-engineered and overfitting model with the fanciest method from the recent trending papers [143, 560, 580, 586]. In practice, the large-scale datasets could be achieved by a massive uptake of smart compressive garments capturing multiple modalities at once (section §III). Examples of simpler smart compressive garments (see figure 8A) are developed by such companies as formsense™, Athos™, Myant™, and asensei™. Large-scale datasets from similar types of data modalities, such as ergonomics tracking for Amazon™ warehouse workers to reduce musculoskeletal disorders [777], could be used in self-supervised learning setting to improve the features learned also for strength training modalities.

Additionally, strength training is missing its "grand challenge" / NeurIPS-level benchmark dataset, for which AI and sports science labs would base their models for and compete against each other. Strength training research could draw inspiration from the "Learn to Move' competition, that is aimed at developing new deep reinforcement learning musculoskeletal models for human locomotion [758]. The converge of strength training modeling with musculoskeletal modeling field (see figure 8B) seems likely in near future as the data and model outputs are essentially the same [465, 466, 693].

Often researchers and data-generating institutions are also hesitant in sharing integral part of their intellectual property, and innovative ways to encourage data sharing is needed. One possible avenue for getting some open-source data is to share a subset of the proprietary dataset essentially as a "marketing tool" or as business development effort, as done for example by Matterport™[7] for 3D indoor data [921], and Qure.ai™ for intracranial hemorrhage (ICH) CT data [140]. Additionally data-only journals have emerged [176, 719] allowing data-only publications count as published articles in bureaucratic institutional key performance indicators (KPIs), and helping to advance the career of the scientists.

The emerging deep reinforcement learning (DRL) models are most likely being applied first to clinical challenges [673, 707, 758, 890], but with collaborative interest from sports scientists, the models developed e.g. with `OpenSIM-RL` [404] could be easily retrained for athlete populations. In practice, this could be done through fine-tuning pre-trained robotic and/or clinical locomotion models with self-supervised learning for smaller athletic datasets (IV B). DRL has been studied in medical prescriptive modeling [501, 620], and allows the modeling of intra- and inter-individual responses to exercise (ambiguous ground truths) [855]; and inclusion of the preferences/constraints of the athlete by learning a set of DRL policies [523]. In other words, the model could be constrained by human decisions, such as how the clinical outcome changes if the patient prefers surgery over a prolonged therapy, and how for example athlete's squat could improve given the athlete's preference for rep ranges [458] and exercise selection [90, 94].

In summary, precision strength training is currently lacking large-scale open-source datasets and the measurement technology with good user experience (UX) to facilitate creation of those datasets. While waiting for the pervasive wearable sensor platforms (e.g. smart compressive garments), initial proof-of-concept datasets with laboratory quality technology could be released as 'Grand Challenges', Kaggle competitions or similar benchmarking dataset, to accelerate the strength training research towards the long-term goal of precision strength training. Larger sports training centres and organisations with existing proprietary datasets, who are able to adopt data-centric business strategy, are probably the ones succeeding over the ones simply hiring individual data scientists [56, 126, 547, 658, 732, 741]. Additionally, the most concepts reviewed here are not unique to strength training, and can be adopted in clinical physiotherapy such as in stroke rehabilitation [5], physiotherapy for pain management [430], sports injury rehabilitation [39], osteoarthritis rehabilitation [125], and orthopaedic surgery rehabilitation [79, 241, 474, 799].

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