

Review

Implementing Meta-Session Autoregulation Strategies for Exercise - A Scoping Review

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ABSTRACT

International Journal of Exercise Science 17(5): 382-404, 2024. Meta-session autoregulation, a personadaptive form of exercise prescription that adjusts training variables according to daily fluctuations in performance considering an individual's daily fitness, fatigue, and readiness-to-exercise is commonly used in sports-related training and may be beneficial for non-athlete populations to promote exercise adherence. To guide refinement of meta-session autoregulation, it is crucial to examine the existing literature and synthesize how these procedures have been practically implemented. Following PRIMSA guidelines a scoping review of two databases was conducted from August 2021 to September 2021 to identify and summarize the selected measures of readiness-toexercise and decision-making processes used to match workload to participants in meta-session autoregulatory strategies, while also evaluating the methodological quality of existing study designs using a validated checklist. Eleven studies reported utilizing a form of meta-session autoregulation for exercise. Primary findings include: (i) readiness-to-exercise measures have been divided into either objective or subjective measures, (ii) measures of subjective readiness measures lacked evidence of validity, and (iii) fidelity to autoregulatory strategies was not reported. Results of the risk of bias assessment indicated that 45% of the studies had a poor-quality score. Existing implementations of meta-session autoregulation are not directly translatable for use in health promotion and disease prevention settings. Considerable refinement research is required to optimize this person-adaptive strategy prior to estimating effects related to exercise adherence and/or health and fitness outcomes. Based on the methodological deficits uncovered, researchers implementing autoregulation strategies would benefit reviewing existing models and frameworks created to guide behavioral intervention development.

KEY WORDS: Individualization, optimization, training variability, behavioral treatment development, health behavior, precision behavioral medicine

INTRODUCTION

Exercise is one of the most frequently prescribed behaviors in both health promotion and disease prevention settings (19). Substantial evidence demonstrates that exercise yields both psychological (45) and physiological benefits (63). Although numerous exercise interventions have been designed and implemented, Dishman et al., (16) reported that 50% of adults engaged

in an exercise program will abandon the activity within one year. More recent reports demonstrate that just 37% of individuals beginning an exercise program will sustain the behavior after one year, despite exhibiting high motivation and possessing knowledge of the benefits of exercise (20). Consistency in exercise behavior may be particularly difficult because of the day-to-day fluctuations in non-training related stressors (33), the series of coordinated actions needed to enact exercise (24) and the variety in individuals' abilities to perform and respond to the effect of this training (30, 66). Thus, due to the complexity associated with exercise behavior, experts have suggested that exercise programs be presented with the flexibility to be person-adaptative, avoiding broad application of one-size-fits-all approaches (9, 11, 51).

Autoregulation is an existing model, conceptualized for sport-related physical training in athletes, that may be useful for guiding flexible, person-adaptive exercise programming for various untrained populations (22, 75). The premise of autoregulation is that the daily training demand should be adjusted accordingly to the individuals perceived performance capabilities. Under experimental conditions, several autoregulatory approaches to exercise have been demonstrated to perform as well as, or superior to programs that utilize a predetermined schedule of training demand to improve outcomes related to strength (10, 27, 43, 46, 81) and body composition (58). Several forms of autoregulation exist and can be categorized based on the time scale with which the measurement and/or adjustment of training variables occurs (within-session and meta-session) (22). Specifically, within-session autoregulation encompasses the use of repetitions in reserve (RIR), rate of perceived exertion (RPE), and velocity-based training (VBT) to adjust training variables, as needed, *during* the training session occurring. At the meta-session level, the use of flexible nonlinear periodization (FNLP) and heart rate variability (HRV)-based training directs that a target training session is selected based on preexercise trainee attributes (i.e., mental/physical readiness, deviation in HRV) and then completed without further adjustments. Given the variety of autoregulatory models, it is important to consider the benefits and limitations of each to identify which model(s) may be most promising to adapt for novice exercisers.

While applying with-in session autoregulation may allow for more instantaneous modifications to training variables (i.e., adjusting exercise selection, number of sets and repetitions, and intensity, and/or duration in real time), there may be limitations in utilizing this method in untrained individuals. Specifically, while VBT uses objective monitoring to guide within-session training adjustments in response to localized muscular fatigue (21, 65), however this method is limited by its specificity to resistance training only and by the availability of costly liner position transducers (i.e., > \$500 per unit), which may be prone to device specific limitations in accuracy (56). Conversely, autoregulatory methods relying on RPE/RIR incur no cost, as ratings are a subjective measure of an individual's perception measure of muscular or total body fatigue. However, perceptual based training has been reported to be less accurate among the untrained populations (71), and in high-repetition sets (23). Thus, RPE/RIR as an autoregulatory method may be more appropriate and effective for trained individuals who can more accurately perceive interoceptive cues and forecast future outcomes in the moment to properly adjust training variables throughout the training session.

The application of meta-session autoregulation, which relies on a single daily decision, may be more manageable for novice individuals who are not yet adept to continuously monitor training responses and appropriately adjust to exercise demands across the session. Instead, meta-session methods first require a pre-exercise assessment. In the case of FNLP, trainers utilize a pre-exercise assessment of mental and physical readiness, which can include a "trial run" of the chosen workload (39). Alternatively, assessments of HRV are conscientiously targeted as a single objective measure that is sensitive to various behavioral (i.e., sleep quality), physiological (i.e., illness), environmental, and psychological (i.e., stress, mood) factors, with the purpose to adjust the training stimulus contingent with observation in high-frequency oscillations in R-R intervals (18, 35). Then based on the pre-exercise assessment, a training session is selected to best match the current condition of each individual, purportedly allowing for high quality performance of the entire session, theoretically without the need for further adjustments to during the training session. It is important to consider, however, that modification or application of meta-session autoregulatory strategies must be guided empirically to best serve the aim of providing person-adaptive programming for novice or at-risk individuals.

In line with published guidelines for appropriately designing and efficiently optimizing behavioral intervention strategies (13), preliminary work must include reviewing and summarizing existing literature to understand how meta-session autoregulation strategies have been implemented to date. That is, a thorough review is likely to provide important insights and gaps in understanding that must be addressed before prematurely testing a strategy (i.e., meta-session autoregulation) within a sample of untrained individuals, which may prove suboptimal without necessary refinements. Given that meta-session autoregulation represents a potential model for person-adaptive programming, we aim to investigate how such strategies have been implemented in research studies under experimental training conditions. By identifying any observed commonalities regarding key implementation considerations, we can provide an initial foundation of knowledge to guide subsequent refinement towards optimization. Therefore, this review aims to identify, summarize, assess the quality, and discuss studies where meta-session autoregulation strategies have been implemented for exercise.

METHODS

Search Strategy

A literature search was conducted between August and September 2021 based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extensions for Scoping Reviews (PRISMA-ScR) (79), ensuring full adherence to the ethical standards outlined by the International Journal of Exercise Science (52). Peer-reviewed articles from August 2000 to the date of the initial search (August 26th, 2021) were retrieved using PubMed and SportsDiscus databases. 'AND' Boolean searches were completed with six terms related to autoregulation ("autoregulation," "autoregulatory," "periodization," "periodized," "flexible non-linear," "flexible nonlinear") in conjunction with eleven terms related to modes of exercise and potential outcomes of exercise ("resistance training,", "strength," "physical activity," "physical therapy,"

"aerobic," "exercise," "endurance," "composition," "mass," "hypertrophy," "training"), resulting in 66 individual searchers per database. No MeSH terms were conducted during this process.

Inclusion Criteria

To be included in the final analysis, articles were (i) written in English, (ii) published between August 2000 and August 2021, (iii) published in a scholarly peer-reviewed journal (iv) utilized any form of meta-session autoregulation for at least one group within any study designs. The first author conducted the full literature search from both databases, screened titles and abstracts, and evaluated the publications that were considered eligible for inclusion. The second author independently repeated the process within the same month, and the two processes were compared to calculate interobserver agreement (IOA). Initial IAO for titles and abstract screening was 96% and 98% respectively. In the event of any discrepancies unresolved by the first two authors, this issue was then referred to the third (senior) author, however an agreement of 100% was after the first 2 authors met for discussion. All authors agreed upon the final list of included articles. The first author conducted and compiled the study's descriptive and performance outcomes independently.

Methodological Quality

The quality of each selected article was assessed using the checklist developed by Downs and Black (17). This tool was selected because it provides a comprehensive assessment of the methodological quality of both randomized and non-randomized studies in health-related research and has been validated as a tool to evaluate the quality of reporting as well as internal and external validity (17). It is made up of 27 criteria, which are related to reporting (10 items), external validity (3 items), internal validity - bias (7 items), internal validity - confounding (selection bias; 6 items), and statical power (1 item). All criteria have a value of 0 to 1, except for two criteria. Criterion 5 allows for a maximum score of 2 points and criterion 27 allows for a max score of 5 points. Criterion 27, "Did the study have sufficient power to detect a clinically important effect where the probability value for a difference being due to chance is less than 5%?" was altered to a 0 to 1 score, based on whether the authors conducted a power analysis to detect a significant clinical effect of at least 0.08, with alpha at 0.05, with a score of 0 meaning "no" and 1 meaning "yes." Thus, an individual study could be scored between 0 and 28 points, with higher scores indicating a stronger methodological quality study. The first author conducted the full assessment independently and used score ranges suggested by Hooper et al., (29) that correspond to levels of quality: Excellent (26-28), Good (20-25), Fair (15-19), and poor (≤14).

RESULTS

Study Selection and Characteristics

The PRISMA flow diagram outlining the literature search strategy is illustrated in Figure 1. The initial search of all databases generated 8,616 titles (4,698 obtained from PubMed and 3,918 from SportsDiscus). After removing duplicate titles, the total was reduced to 2,165 remained for initial review. Upon screening the titles and abstracts, 40 articles were considered eligible for a full text

read. An additional 6 articles were added based on screening the references of the 40 articles that were considered eligible for a full review. Of the 46 articles read in full, 34 were excluded based on the following criteria: intervention investigated within session autoregulation (17 articles), did not include any identifiable form of autoregulation (16 articles), publication was limited to an abstract (1 article). Thus, in total, 11 studies were included for review. Among these included studies, seven included a condition guided by FNLP and four studies included a condition guided by HRV. Sample sizes ranged from 16 to 60 participants. Six studies included physically active individuals, however thresholds towards this classification varied (i.e., performing regular physical activity for at least 6 months for a minimum of 150 minutes per week (48)). Four studies included untrained individuals and one study had specifically included collegiate athletes. Regarding FNLP, four studies only included resistance training exercise, while three utilized concurrent training, with variability in programing variables. All HRV-based training studies targeted only aerobic exercise. Detailed study characteristics can be found in Table 1.

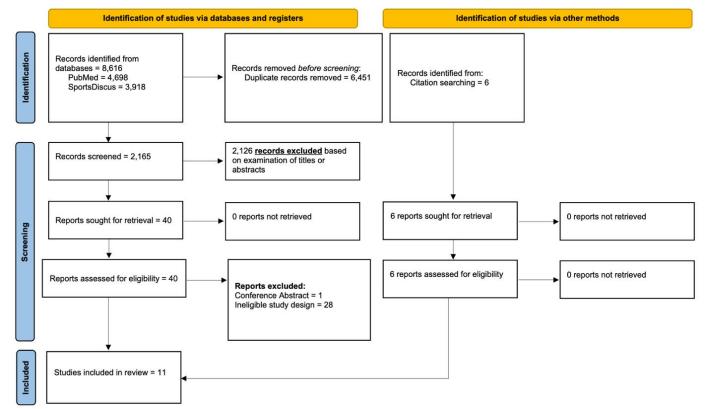


Figure 1. PRISMA flowchart of screening, exclusion, and inclusion criteria.

Author group (year)	Sample description; Study design, duration, training frequency, and adherence (%)	Selection Process and Training overview
	Flexible nonline	Flexible nonlinear periodization (FNLP)
		Can choose order of the session RMs based on energy levels.
McNamara et al. 2010	16 untrained males (n=12) females (n=4) RCT, 12 weeks, 3 times per week, NM	Mesocycle 1 (4 weeks): 7 exercises 7 sets at 10, 15, and 20RMs Mesocycle 2 (4 weeks): 10 exercises 10 sets at 10, 15, and 20RMs Mesocycle 3 (4 weeks): 15 exercises 15 sets at 10, 15, 20RMs
	Ŭ	Can choose order of the session RMs based on mood, preference and energy levels.
McNamara et al. 2013	20 untrained males (n=13) females (n=7) RCT, 13.5 weeks, 2 times per week, NM	Mesocycle 1 (3.5 weeks): 6 exercises 2 sets at 5, 8, 10, 12, 15RMs Mesocycle 2 (4 weeks): 10 exercises 1 set at 6, 7, 8, 9, 10, 11, 12, 13RMs Mesocycle 3 (4 weeks): 11 exercises 1 set at 10, 11, 12, 14, 16, 18, 19, 20RMs 15 minutes of cycling Mesocycle 4 (2 weeks): 11 exercises 1 set at 5, 8, 10, 12, 15RMs
		One group chose 15-minute cycling sessions with either 10 or 45 seconds of maximal effort throughout the study.

Author group (year)	Sample description; Study design, duration, training frequency, and adherence (%)	Selection Process and Training overview
	Flexible nonline	Flexible nonlinear periodization (FNLP)
Da Silva et al. 2016	121 untrained men aged from 18-50 RCT, 12 weeks, 4 times per week, NM	Not Reported Weeks 1-12 Endurance: 2 sets of 12-15 reps 60% 1RM Hypertrophy: 3 sets of 3-5 reps 80% 1RM Strength: 4 sets of 3-5 reps 90% 1RM Power: 6 sets of 5 reps 40% 1RM
Colquhoun et al. 2016	25 resistance trained individuals aged 23.1 ± 4.1 RCT, 9 weeks, 3 times per week, 99%	Can choose the order of a ' hypertrophy' ,' strength' , or ' power' day each week based on motivation to train. <i>Weeks 2-4</i> 8 repetitions (hypertrophy day) and 3 repetitions (strength day) <i>Weeks 5-7</i> 6 repetitions (hypertrophy day) and 2 repetition (strength day) <i>Weeks 8-9</i> 5 repetitions (hypertrophy day) and 1 repetition (strength day) <i>Dower day followed a 1 P model progressing from 80% to 90% from</i>

Author group (year)	S	Selection Process and Training overview
	irequency, and addreame (%) Flexible nonlinear	Flexible nonlinear periodization (FNLP)
		Not Reported
		30 minutes of aerobic exercise (bicycle or treadmill) followed by 30 minutes strength exercise (8 total exercises)
- F	of puysically active, posuriertopausat women aged 61.6 ± 6.4	Strength training:
koarigues et al. 2019	RCT, 12 weeks, 3 times per week, NM	2 sets of 10–12RM
		Aerobic training:
		50% of the HRM
		60% of the HRM
		70% of the HKM
		Not Reported
		Strength training:
		2 sets of 5-7 RM
Medeiros et	04 pnysicany аспуе мотеп адеи э0-70	2 sets of 15–12KW 2 sets of 15–17RM
al. 2020	RCT; 17 weeks; 3 times per week, 90.1%	Aerobic training:
		RPE from 15 to 16 and 70% of the HRR RDE from 13 to 14 and 60% of the HRB
		RPE from 11 to 12 and 50% of the HRR

Author	Sample description;	
group (year)	Study design, duration, training frequency, and adherence (%)	Selection Frocess and Training overview
	Flexible non	Flexible nonlinear periodization (FNLP)
	32 male (n=15) and female (n=17) D3	Choose workouts listed below that aligned with state of readiness score.
Walts et al. 2021	collegiate lacrosse athletes RCT, 8 weeks, 3 times per week, NM	2 repeated 4-week blocks of full body training (specifics not given) Low Intensity High Volume Low Volume High Intensity
	Heart 1	Heart Rate Variability (HRV)
	30 healthy recreational male runners	Training imposed according to recovery status each morning.
Kiviniemi et al. 2007	RCT, 4 weeks, Varied, 85% (3 dropouts, 1 excluded)	3-day cycle repeated during weeks 1-4 Low intensity: 65% of HRM High intensity: 85% of HRM Rest
	60 healthy untrained males (n=24) and females (n=36)	Training imposed according to recovery status each morning.
Kiviniemi et al. 2010	RCT, 8 weeks, Varied, 88% (4 dropouts, 3 excluded)	Weeks 1-8 Moderate intensity: 70% HR _{peak} Vigorous intensity: 85% HR _{peak} Rest

Author group	Sample description; Study design, duration, training	Selection Process and Training overview
(year)	frequency, and adherence $(\%)$	
	Heart I	Heart Rate Variability (HRV)
		Training imposed according to recovery status each morning.
	17 trained male cyclists	8 Weeks
Iavaloves et	2	Low intensity: 120-180 minutes below ventilatory threshold 1
al. 2018	RCT, 12 weeks, Varied; NM	Moderate intensity: 40 minutes between ventilatory threshold 1 and 2 High intensity: 30 minutes at ventilatory threshold 2
		High intensity interval intensity: 4x8 minutes greater than ventilatory threshold 2
		Rest
		Training imposed according to recovery status each morning.
-	20 well trained cyclists aged 18-46	8 Weeks
Javaloyes et al. 2020	RCT, 10 weeks, Varied, 75% (1 dropout, 4	Low intensity: Less than ventilatory threshold 1 High intensity: Creater than youtilatory threshold 2
	excluaea)	High intensity interval intensity: Greater than ventilatory threshold 2
		Rest

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Methodological Quality of Included Studies

Quality scores are summarized in Table 2. The average quality score was 16 ('fair') out of 28. Point deductions were generally due to reporting adverse events (N = 16), blinding (N = 15), reliable compliance (N = 16), reporting the specific details about the recruitment population (N = 14), including recruitment timeframes.

Author group (year)	Reporting	External validity	Bias	Confounding	Power	Overall	Rating*
	0-11	0-3	0-7	0-6	0-1	0-28	-
		Flexible nor	nlinear p	periodization			
McNamara et al. 2010	4	1	4	5	0	14	Poor
McNamara et al. 2013	3	1	4	4	1	13	Poor
da Silva et al. 2016	8	0	4	2	0	14	Poor
Colquhoun et al. 2016	9	0	5	3	1	18	Fair
Rodrigues et al. 2019	6	0	4	2	1	13	Poor
Medeiros et al. 2020	6	0	4	3	0	13	Poor
Walts et al. 2021	9	2	4	5	1	21	Good
		Heart	rate var	riability			
Kiviniemi et al. 2007	9	0	4	3	1	17	Fair
Kiviniemi et al. 2010	9	0	4	3	1	17	Fair
Javaloyes et al. 2018	8	0	4	3	0	15	Fair
Javaloyes et al. 2020	9	0	4	3	0	16	Fair

Table 6. Results of Downs and Black checklist for assessment of methodological of	quality.

*According to Hooper et al., (2008) recommendations Excellent (26-28), Good (20-25), Fair (15-19), and poor (\leq 14).

Structural Features of Meta-Session Autoregulation

Readiness Metrics to Guide Training Decisions: Descriptions of subjective readiness under FNLP varied. In three studies (14, 48, 61), detailed descriptions of readiness were absent. In the introduction, Da Silva et al., (14) only contextualized FNLP in the introduction as "programing that may vary daily or weekly, depending on the physical and psychological state of the individual" (p. 2). Similarly, Medeiros et al., (48) described FNLP in that "daily workload intensity and volume are based on the participants pre-exercise mental/physical state" (p. 1). Rodrigues et al., (61) also provided a limited description of readiness as "allowing the subject to take into consideration their daily variation in physiological and mental conditions" (p. 3). In these cases, the specific constructs measured to assess readiness are unknown.

Subjective readiness was described in four studies that implemented FNLP (10, 46, 47, 81), with variation in operationalization. McNamara and Stearne (46) implemented a single 0-10 energy scale, where zero represented no energy, and ten represented "full motivation and maximum energy to work out" (p.10). In a later study focused on concurrent training McNamara and Stearne (47) instructed participants to consider mood, preference, and energy levels to select duration of aerobic training and the intensity for resistance training. Colquhoun et al., (10) instructed participants to assess their motivation to train using a 5-point Likert scale before

selecting their training session. Walts et al., (81) asked collegiate athletes to use a mobile application (TeamBuildr) to rate their state of readiness using a single pre-exercise question: "Based on how your body feels and your current mindset, how ready are you for today's training?". The outcome 'feel or mindset' was then rated as 'good, fair or, poor.' None of the studies included validated items or surveys when measuring readiness or provided empirical or theoretical support for the chosen indices.

Objective measures of readiness were exclusively based on HRV, with specific focus on high frequency (HF) power (38), or root-mean-squat differences (31, 32, 37) metrics. In each case, the time of the HRV measurement was consistently completed under the following conditions: at home, in the morning after awakening, and after voiding the bladder. The positioning and duration of the HRV measurements varied as less burdensome procedures were adopted between earlier and later studies. Specifically, Javaloyes et al., (31) required participants take their measurement in a supine position for 3 minutes. However, later, Javaloyes et al., (32) required participants take their measurement in a supine position for 90 seconds. Similarly, Kiviniemi et al., (38) first required participants to measure HRV first in a seated position for 3 minutes. HRV was determined using commercially available heart rate monitors with a chest strap (31, 38), a "tailored noncommercial" heart rate monitor (37), or the HRVTraining smartphone application, which leverages the camera flash over an individual's fingertip to measure heart rate and HRV (32).

Process of Matching Readiness Metric(s) to Bout Decisions: Within the FNLP literature, the procedures of appropriately matching readiness to a training bout have varied with limited, evidence-based directives. Three studies did not include the methods by which individuals selected (or were assigned) each session throughout the training program (14, 48, 61). While not explicitly stated, it is reasonable to presume that Colquhoun et al., (10) allowed participants to self-select which training session (i.e., hypertrophy, power, strength) to complete each day. McNamara and Stearne (46, 47) similarly allowed participants to self-select training sessions, but the selection process became more restricted through the process of elimination (i.e., after competition of the 10RM sessions, these sessions could no longer be chosen), such that participants "would be required to complete the workouts that they may have been previously avoiding" (p.20) (46) or "toward the end of a mesocycle, subjects had fewer options." They eventually were required to complete the workouts that had been avoided earlier" (p. 1466) (47). Walts et al., (81) utilized a color-coded process. "Good", "fair", and "poor" state of readiness scores were characterized as 'green', 'yellow', and 'red', respectively, Selection of the green or vellow ratings triggered the application to present either a high or low volume and intensity workout, respectively. Red ratings triggered a prompt to avoid training that day and rest. Once a session was completed, it was no longer available to be selected within a 4-week block. No studies utilizing subjective readiness scores included evidence of fidelity to the FNLP framework (i.e., that the workload performed did correspond to readiness).

In all HRV-based training studies, the session to perform was imposed on individuals based exclusively on their HRV in the context of rolling averages to determine "recovery status" (31, 32, 37, 38). Kiviniemi et al., (38) defined an under recovered state as a daily score lower than the rolling 10-day average of HF power, calculated as the standard deviation of the 10-day HF power subtracted by the 10-day average HF power. In two studies, a seven-day rolling average of the natural logarithm of the root-mean-square differences (LnRMSDD_{7dav-roll-avg}) - obtained by calculating the consecutive time difference between heartbeats - in combination with the smallest worthwhile change was the measurement approach to interpret recovery status (31, 32). One study, (37) examined the smallest worthwhile change of LnRMSDD7day-roll-avg, calculated as "mean $\pm 0.5 \times SD$," to determine participant recovery status (a SD1 daily value lower than the "SD-mean" of a 10-day rolling reference value = under-recovered). In all instances, the same decision-making schema developed by Kiviniemi et al., (38) was implemented with each beginning with an initial low-intensity training session followed by a high-intensity training session regardless of a participants HRV score. Then, if the HRV score was below the rolling average range, a low-intensity training was prescribed for the third session. Further decreases in HRV resulted in a rest day being prescribed. A maximum of 2 rest days were allowed, with a low-intensity training session assigned on the following day regardless of the HRV score. If the HRV score after the first two sessions was above or within 'recovery' range, a high intensity session was assigned, but only for 2 consecutive days, and thereafter a low intensity training bout was prescribed. Additionally, after nine consecutive days of training, a day of rest was prescribed regardless of the HRV score. None of the studies utilizing objective readiness scores included evidence of fidelity to the HRV framework, similar to subjective metrics of readiness.

Physical Performance and Psychobehavioral Outcomes: A majority of the included studies assessed performance with various measures utilized for anaerobic and aerobic outcomes (10, 14, 31, 32, 37, 38, 47, 48, 81). Less frequently measured were psychosocial, cognitive, or perceptual outcomes, such as post-session 'fatigue sensation' (37, 38) post-training quality of life (48), and performance satisfaction (10). Additionally, none of the included studies evaluated any health outcomes. Further detailed reporting of outcome measures can be found in Table 3.

Author group (year)	Anaerobic Performance Outcomes	Aerobic Performance	Psychobehavioral
		Outcomes	Outcomes
	Flexible nonlinear periodization	dization	
McNamara et al. 2010	1RM Leg Press: +33%	None Measured	None Measured
McNamara et al. 2013	<pre>1RM Chest Press: No cycling +35%; With cycling +29% Long Jump: no cycling +3%; With cycling +10%</pre>	None Measured	None Measured
Da Silva et al. 2016	 1RM Bench Press: +14% 1RM Leg Press: +24% Vertical Squat: -2% Counter Movement Jump: -3% 	None Measured	None Measured
Colquhoun et al. 2016	<pre>1RM Bench Press: +7% 1RM Squat: +12% 1RM Deadlift: +9%</pre>	None Measured	Motivation: 3.5 ± 0.6 Satisfaction: 4.1± 0.5
Rodrigues et al. 2019	None Measured	None Measured	None Measured
Medeiros et al. 2020*	1RM Bench Press: +20% 1RM Leg Press: +20%	VO2peak: 11% Walk Test: 3%	Quality of Life: +4.2%
Walts et al. 2021	1RM Leg Press: +33%	None Measured	None Measured

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Author group (year)	Anaerobic Performance Outcomes	Aerobic Performance Outcomes	Psychobehavioral Outcomes
	Heart Rate Variability	iability	
Kiviniemi et al. 2007	None Measured	VO_{2max} : +7%	Fatigue: 4.3 ± 1.3
Kiviniemi et al. 2010	None Measured	VO _{2peak} : HRV-I men +8% HRV-I women +8% HRV-II women +7%	Fatigue: HRV-I men 5.2 ± 1.4 HRV-I women 4.2 ± 1.8 HRV-II women 3.6 ± 1.2
Javaloyes et al. 2018	None Measured	VO ^{2max} : 0%	None Measured
Javaloyes et al. 2020	None Measured	VO _{2max} : +6%	None Measured
Note: 1RM= 1 repetition 1 aerobic exercise test	Note: 1RM= 1 repetition maximum, VO _{2max} = maximal oxygen uptake, VO _{2peak} = highest valued attained during a maximal aerobic exercise test	ake, VO _{2peak} = highest valued att	ained during a maximal

http://www.intjexersci.com

*Data estimated based on bar graph

DISCUSSION

The present review aimed to characterize how researchers have implemented meta-session autoregulation strategies for exercise. From this summary, several key findings emerged. Within the reviewed literature, readiness – the metric purported to guide training-related decisions – has been measured using either strictly objective (HRV) or subjective approaches. However, none of the studies within this review provided information on the validity of the implemented measures of readiness. Similarly, participants' fidelity to the respective autoregulatory strategies are seemingly assumed, with no supporting empirical evidence presented across studies. These gaps correspond to the poor-to-fair ratings of quality observed across studies. The following discussion provides suggestions to improve the quality and usability of future research directed toward meta-session autoregulation.

Across the existing literature, indices of readiness were obtained using either objective or subjective approaches, both of which present with important strengths and limitations to consider. Objective approaches are often selected as a means of minimizing several biases that affect the validity and reliability of subjective measures, such as the measure's sensitivity and/or individuals' subjectivity (67). Unfavorable changes in HRV, for instance, are purportedly indicative of both physiological and psychological determents (18, 35), offering a means of accounting for both domains without the potential for individuals to over or under state their moods, emotions, or stress levels. Individuals may also find objective measures easier to monitor and interpret, as thresholds are often utilized to quantify physiological and performance capabilities, which then can inform diagnostic testing and training prescriptions (60, 70). Measuring the physiological status of an individual partaking in an exercise program is commonly recommended (15), despite being known to be time-consuming while also relying heavily on medical examinations that incur additional financial costs (41). However, to date, emerging physiological monitoring methods - such as HRV - are becoming increasingly popular due to decreased product costs and increased portability that allow for the opportunity to measure real-time physiological status (8).

Despite these improvements in more accessible devices measuring objective markers, limitations still exist. Researchers have noted inconsistent reliability between different conditions, error due to system miscommunication, with additional implications for battery life, data and software management (1, 55, 69). Further, relying purely on objective measures of readiness using wearable devices may distract practitioners from the participant in front of them and undermines the ability of participants partaking in exercise to innately integrate and process their own perceptions accurately (2, 68). The potential also exists for incongruency between objective and subjective reports, such that an individual's own perceptions and performance differ substantially from the interpretations based on objective feedback. For example, a previous study in rugby athletes found objective measures from self-organizing maps and percentage of high-intensity heart rate to have poor fit with ratings of perceived exertion (RPE) in a tournament setting (4), risking athletes being removed from competition despite feeling good and performing well. Similarly, reliability in predicting recovery status was observed to

be poor between HRV and subjective scores from the Short Recovery and Stress Scale for Sports or session RPE (25, 42). Researchers have also previously reported approximately 50% unexplained variance between objective heart rate-derived measures and session RPE (82). Such incongruency has also been documented in clinical settings - for example, those with somatic symptom disorder subjectively report physiological symptoms (e.g., body pain, fatigue, perceived disturbances in cardiovascular or gastrointestinal function) in absence of an objective biological cause (40). Participants that do not fully understand or agree with the guidance procedures (due to incongruency) are unlikely to fully and appropriately engage with the process and may be more open to providing misleading readiness ratings (12, 74). To reduce the possibility of incongruency, consideration of both objective and subjective indices should be explored. Previously Saw, Main and Gastin (68) found that subjective measures appear to report training stress with similar or superior sensitivity and consistency when compared with common objective measures concluding that, although subjective and objective monitoring are distinct in acquiring information (and their interpretations do not always agree) they can complement each other. Therefore, it seems important to distinguish when subjective perceptions are sufficient to determine readiness and when complementary objective information is needed to properly align the training demand to the individual.

Limiting our ability to make informed decisions on whether to use objective, subjective, or combined indices of readiness for meta-session autoregulation is the lack of evidence for validity. Based on the current findings, the previously applied indices of readiness appear to solely rely on *face validity* (i.e., indices appear suitable for their aims). In support of face validity, the variety of subjective constructs measured for FNLP do align with commonly reported barriers and determinants of exercise in the general and untrained population, such as motivation, stress, and energy levels (26, 36, 83). In later research, Strohacker and colleagues used inductive quantitative and qualitative approaches to define dimensions of readiness as including affective states (moods/emotions), activation states (energy/fatigue), physical states (bodily sensations, such as discomfort, pain, hunger/satiety, hydration), perceptions of physical fitness, and motivation (motivational type, mental focus) (76, 77). Thus, to achieve *content validity* (i.e., test is fully representative of all aspects of the construct), future instruments should account for the multivariate nature of readiness.

Instruments designed specifically to assess readiness should also strive to demonstrate *criterion validity* via prediction of relevant outcomes. Prior research has shown that readiness-related constructs (e.g., mood/emotional state, energy/fatigue ratings, physical condition) experienced in pre-exercise contexts have predicted affective valence (pleasure vs. displeasure) during acute exercise (73) or have been cited as influencing affective ratings during exercise using 'talk aloud' procedures in a laboratory setting (62) and recreation facility exit surveys conducted in a university setting (3). Finally, readiness assessment instruments must be examined for *construct validity*, which refers to the degree to which an instrument measures the trait or theoretical construct that it is intended to measure (6). Recent work by Keegan et al., (34) and Summers et al., (78) has demonstrated both convergent and discriminant validity (subtypes supporting construct validity) of the *Acute Readiness Monitoring Scale;* scores showed sufficient associations

with existing validated instruments for related constructs, and responsiveness to the effects of acute sleep deprivation while also relating to associated changes in awakening responses in cortisol and cognitive task performance. While the *Acute Readiness Monitoring Scale* was developed for more generalized readiness states for military populations, five of its nine subscales should be relevant to exercise: physical readiness ("I am physically fit"), physical fatigue ("I am fatigued", "my muscles are sore"), cognitive readiness ("I can focus well"), cognitive fatigue ("I am mentally tired"), and threat-challenge readiness ("I can handle unpleasant feelings"). As such, research is warranted to assess the utility of this scale in exercise settings.

A particular gap within the meta-session autoregulation literature is that no researcher has presented evidence of fidelity for in matching participants' readiness to training demand (i.e., low readiness followed with a low demanding session). Intervention fidelity refers to the extent to which a behavioral intervention was designed, implemented and received as intended (49). Researchers may have assumed both measurement validity and intervention fidelity based on generally favorable physiological and performance outcomes. Further, providing a relatively rigid decision guide or specific directives (flow chart for HRV-based training; color-coded application for FNLP) may minimize participants' cognitive burden, which is an important consideration for buy-in and behavioral enactment (57). However, the provision of autonomy (noted for the majority of FNLP-based studies) has strong theoretical support regarding behavioral adherence (64). Unfortunately, individuals regularly depart from rational decisionmaking due to several biases and heuristics (mental shortcuts employed to reduce complex, deliberate thought processes into a more time-efficient process) (5, 59, 80). Although no study in this review mention such constructs, Colquhoun et al., (10) may have been attempting to mitigate biased decision-making when color-coding workouts as 'green,' 'red,' and 'blue,' rather than using the sessions' outcome descriptors (hypertrophy, strength, power). Bias mitigation may have also been intended when preventing participants from repeating a given session upon completion (i.e., choices became more restricted over time) (46, 47). Beyond these assumptions, however, explicit assessment and reporting of fidelity in future meta-session autoregulation studies is critical as poor fidelity increases the risk of type 1 and 2 errors, resulting in spurious conclusions about intervention effectiveness (49). Further, assessing fidelity can facilitate easier replication, and implementation of behavioral interventions in real-world settings (44).

To enhance the development and refinement of meta-session autoregulation, it is important to adopt a flexible and iterative approach for pre-efficacy research (13). While randomized controlled trials are considered the standard in testing treatment efficacy, relying solely on them during early-stage development can hinder creativity, stifle discovery, and result in ineffective treatments. Additionally, the time-consuming nature of randomized efficacy trials can render outcomes irrelevant due to technological advancements or new discoveries, possibly limiting the utilization of objective measures of readiness (53). Therefore, there is a need for designs that are both rapid and robust during these early pre-efficacy stages. Researchers implementing meta-session autoregulation should strongly consider these authors' recommendations to utilize existing frameworks and checklists to assess fidelity and improve methodological rigor (e.g.,

NIH Behavior Change Consortium Treatment Fidelity Framework (7), Medical Research Council guidance on process evaluations (50), Template for Intervention Description and Replication Checklist (28).

Conclusion: The current review aimed to understand and summarize basic elements of metasession autoregulation, a key step in early-stage research towards intervention optimization (13). Despite general demonstrations of physiological benefits, research in meta-session autoregulation lacks validation of readiness-related constructs, which limits progress in optimizing how readiness is measured (objective, subjective, both). A widespread lack of fidelity assessment further hinders the translation and replication of this strategy in health promotion and clinical settings, as favorable outcomes cannot yet be confidently linked to the process of matching exercise demand to individual readiness. Thus, substantial pre-efficacy research is needed, which stands to benefit from multiple discipline collaboration between experts in periodization, exercise physiology, health psychology, and behavioral intervention (72).

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REFERENCES

1. Baig MM, Gholamhosseini H, Moqeem AA, Mirza F, Lindén M. A systematic review of wearable patient monitoring systems – Current challenges and opportunities for clinical adoption. J Med Syst 41(7): 115, 2017.

2. Balague N, Hristovski R, Almarcha M, Garcia-Retortillo S, Ivanov PC. Network physiology of exercise: Vision and perspectives. Front Physiol 11: 611550, 2020.

3. Beaumont CT, Ferrara PM, Strohacker K. Exploring determinants of recalled in-task affective valence during recreational exercise. Physiol Behav 230: 113261, 2021.

4. Blair MR, Body SF, Croft HG. Relationship between physical metrics and game success with elite rugby sevens players. Int J Perform Anal Sport 17(4): 418-428, 2017.

5. Blumenthal-Barby JS. Biases and heuristics in decision making and their impact on autonomy. Am J Bioeth 16(5): 5-15, 2016.

6. Bolarinwa OA. Principles and methods of validity and reliability testing of questionnaires used in social and health science researches. Niger Postgrad Med J 22(4): 195-201, 2015.

7. Borrelli B, Sepinwall D, Ernst D, Bellg AJ, Czajkowski S, Breger R, DeFrancesco C, Levesque C, Sharp DL, Ogedegbe G, Resnick B, Orwig D. A new tool to assess treatment fidelity and evaluation of treatment fidelity across 10 years of health behavior research. J Consult Clin Psychol 73(5): 852-860, 2005.

8. Bunn JA, Navalta JW, Fountaine CJ, Reece JD. Current state of commercial wearable technology in physical activity monitoring 2015-2017. Int J Exerc Sci 11(7): 503-515, 2018.

9. Chevance G, Perski O, Hekler EB. Innovative methods for observing and changing complex health behaviors: Four propositions. Transl Behav Med 11(2): 676-685, 2021.

10. Colquhoun RJ, Gai CM, Walters J, Brannon AR, Kilpatrick MW, D'Agostino DP, Campbell BI. Comparison of powerlifting performance in trained men using traditional and flexible daily undulating periodization. J Strength Cond Res 31(2): 283-291, 2017.

11. Conroy DE, Lagoa CM, Hekler E, Rivera DE. Engineering person-specific behavioral interventions to promote physical activity. Exerc Sport Sci Rev 48(4): 170-179, 2020.

12. Coyne JOC, Gregory Haff G, Coutts AJ, Newton RU, Nimphius S. The current state of subjective training load monitoring – A practical perspective and call to action. Sports Med Open 4: 58, 2018.

13. Czajkowski SM, Powell LH, Adler N, Naar-King S, Reynolds KD, Hunter CM, Laraia B, Olster DH, Perna FM, Peterson JC, Epel E, Boyington JE, Charlson ME. From ideas to efficacy: The orbit model for developing behavioral treatments for chronic diseases. Health Psychol 34(10): 971-982, 2015.

14. Da Silva DG, Vilaca-Alves. J, de Souza. LL, dos Santos S, Figueiredo. T, Paz. AG, Willardson MJ, Miranda H. Effects of daily and flexible non-linear periodization on maximal and submaximal strength, vertical jump, and speed performance of Brazilian army skydivers. Int J Sports Exerc Med 2(4): 1-6, 2016.

15. Davison RR, Van Someren KA, Jones AM. Physiological monitoring of the Olympic athlete. J Sports Sci 27(13): 1433-1442, 2009.

16. Dishman RK. Compliance/adherence in health-related exercise. Health Psychol 1(3): 237-267, 1982.

17. Downs SH, Black N. The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. J Epidemiol Community Health 52(6): 377-384, 1998.

18. Fatisson J, Oswald V, Lalonde F. Influence diagram of physiological and environmental factors affecting heart rate variability: An extended literature overview. Heart Int 11(1): e32-e40, 2016.

19. Febbraio MA. Exercise metabolism in 2016: Health benefits of exercise - more than meets the eye! Nat Rev Endocrinol 13(2): 72-74, 2017.

20. Gjestvang C, Abrahamsen F, Stensrud T, Haakstad LAH. Motives and barriers to initiation and sustained exercise adherence in a fitness club setting – A one-year follow-up study. Scand J Med Sci Sports 30(9): 1796-1805, 2020.

21. Gonzalez-Badillo JJ, Sanchez-Medina L. Movement velocity as a measure of loading intensity in resistance training. Int J Sports Med 31(5): 347-352, 2010.

22. Greig L, Stephens Hemingway BH, Aspe RR, Cooper K, Comfort P, Swinton PA. Autoregulation in resistance training: Addressing the inconsistencies. Sports Med 50(11): 1873-1887, 2020.

23. Hackett DA, Cobley PS, Halaki M. Estimation of repetitions to failure for monitoring resistance exercise intensity: Building a case for application. J Strength Cond Res 32(5): 1352-1359, 2018.

24. Hagger MS. Habit and physical activity: Theoretical advances, practical implications, and agenda for future research. Psychol Sport Exerc 42: 118-129, 2019.

25. Hauer R, Tessitore A, Knaus R, Tschan H. Lacrosse athletes load and recovery monitoring: Comparison between objective and subjective methods. Int J Environ Res Public Health 17(9): 3329, 2020.

26. Heesch KC, Brown DR, Blanton CJ. Perceived barriers to exercise and stage of exercise adoption in older women of different racial/ethnic groups. Women Health 30(4): 61-76, 2000.

27. Helms ER, Byrnes RK, Cooke DM, Haischer MH, Carzoli JP, Johnson TK, Cross MR, Cronin JB, Storey AG, Zourdos MC. RPE vs. Percentage 1rm loading in periodized programs matched for sets and repetitions. Front Physiol 9: 247, 2018.

28. Hoffmann TC, Glasziou PP, Boutron I, Milne R, Perera R, Moher D, Altman DG, Barbour V, Macdonald H, Johnston M, Lamb SE, Dixon-Woods M, McCulloch P, Wyatt JC, Chan A-W, Michie S. Better reporting of

interventions: template for intervention description and replication (tidier) checklist and guide. BMJ 348: g1687, 2014.

29. Hooper P, Jutai JW, Strong G, Russell-Minda E. Age-related macular degeneration and low-vision rehabilitation: A systematic review. Can J Ophthalmol 43(2): 180-187, 2008.

30. Hubal MJ, Gordish-Dressman H, Thompson PD, Price TB, Hoffman EP, Angelopoulos TJ, Gordon PM, Moyna NM, Pescatello LS, Visich PS, Zoeller RF, Seip RL, Clarkson PM. Variability in muscle size and strength gain after unilateral resistance training. Med Sci Sports Exerc 37(6): 964-972, 2005.

31. Javaloyes A, Sarabia JM, Lamberts RP, Moya-Ramon M. Training prescription guided by heart rate variability in cycling. Int J Sports Physiol Perform 14(1): 23-32, 2019.

32. Javaloyes A, Sarabia JM, Lamberts RP, Plews D, Moya-Ramon M. Training prescription guided by heart-rate variability vs. block periodization in well-trained cyclists. J Strength Cond Res 34(6): 1511-1518, 2020.

33. Justine M, Azizan A, Hassan V, Salleh Z, Manaf H. Barriers to participation in physical activity and exercise among middle-aged and elderly individuals. Singapore Med J 54(10): 581-586, 2013.

34. Keegan RJ, Flood A, Niyonsenga T, Welvaert M, Rattray B, Sarkar M, Melberzs L, Crone D. Development and initial validation of an acute readiness monitoring scale in military personnel. Front Psychol 12: 738609, 2021.

35. Kim HG, Cheon EJ, Bai DS, Lee YH, Koo BH. Stress and heart rate variability: A meta-analysis and review of the literature. Psychiatry Investig 15(3): 235-245, 2018.

36. King AC, Castro C, Wilcox S, Eyler AA, Sallis JF, Brownson RC. Personal and environmental factors associated with physical inactivity among different racial-ethnic groups of U.S. Middle-aged and older-aged women. Health Psychol 19(4): 354-364, 2000.

37. Kiviniemi AM, Hautala AJ, Kinnunen H, Nissila J, Virtanen P, Karjalainen J, Tulppo MP. Daily exercise prescription on the basis of HR variability among men and women. Med Sci Sports Exerc 42(7): 1355-1363, 2010.

38. Kiviniemi AM, Hautala AJ, Kinnunen H, Tulppo MP. Endurance training guided individually by daily heart rate variability measurements. Eur J Appl Physiol 101(6): 743-751, 2007.

39. Kraemer WJ, Fleck SJ. Optimizing strength training: Designing nonlinear periodization workouts. Champaign, IL: Human Kinetics; 2007.

40. Kurlansik SL, Maffei MS. Somatic symptom disorder. Am Fam Physician 93(1): 49-54, 2016.

41. Lac G, Maso F. Biological markers for the follow-up of athletes throughout the training season. Pathol Biol (Paris) 52(1): 43-49, 2004.

42. Lukonaitienė I, Conte D, Paulauskas H, Pliauga V, Kreivytė R, Stanislovaitienė J, Kamandulis S. Investigation of readiness and perceived workload in junior female basketball players during a congested match schedule. Biol Sport 38(3): 341-349, 2021.

43. Mann JB, Thyfault JP, Ivey PA, Sayers SP. The effect of autoregulatory progressive resistance exercise vs. linear periodization on strength improvement in college athletes. J Strength Cond Res 24(7): 1718-1723, 2010.

44. Mars T, Ellard D, Carnes D, Homer K, Underwood M, Taylor SJC. Fidelity in complex behaviour change interventions: A standardised approach to evaluate intervention integrity. BMJ Open 3(11): e003555, 2013.

45. McKercher C, Sanderson K, Schmidt MD, Otahal P, Patton GC, Dwyer T, Venn AJ. Physical activity patterns and risk of depression in young adulthood: A 20-year cohort study since childhood. Soc Psychiatry Psychiatr Epidemiol 49(11): 1823-1834, 2014.

46. McNamara JM, Stearne DJ. Flexible nonlinear periodization in a beginner college weight training class. J Strength Cond Res 24(1): 17-22, 2010.

47. McNamara JM, Stearne DJ. Effect of concurrent training, flexible nonlinear periodization, and maximal-effort cycling on strength and power. J Strength Cond Res 27(6): 1463-1470, 2013.

48. Medeiros LHL, Sandbakk SB, Bertazone TMA, Bueno Júnior CR. Comparison of periodization models of concurrent training in recreationally active postmenopausal women. J Strength Cond Res 36(4): 977-983, 2022.

49. Moncher FJ, Prinz RJ. Treatment fidelity in outcome studies. Clin Psychol Rev 11(3): 247-266, 1991.

50. Moore G, Audrey S, Barker M, Bond L, Bonell C, Cooper C, Hardeman W, Moore L, O'Cathain A, Tinati T, Wight D, Baird J. Process evaluation in complex public health intervention studies: The need for guidance. J Epidemiol Community Health 68(2): 101-102, 2014.

51. Nahum-Shani I, Smith SN, Spring BJ, Collins LM, Witkiewitz K, Tewari A, Murphy SA. Just-in-time adaptive interventions (jitais) in mobile health: Key components and design principles for ongoing health behavior support. Ann Behav Med 52(6): 446-462, 2018.

52. Navalta JW, Stone WJ, Lyons TS. Ethical issues relating to scientific discovery in exercise science. Int J Exerc Sci 12(1): 1-8, 2019.

53. Norgeot B, Glicksberg BS, Butte AJ. A call for deep-learning healthcare. Nat Med 25(1): 14-15, 2019.

54. Nuuttila OP, Nikander A, Polomoshnov D, Laukkanen JA, Hakkinen K. Effects of hrv-guided vs. predetermined block training on performance, hrv, and serum hormones. Int J Sports Med 38(12): 909-920, 2017.

55. Peake JM, Kerr G, Sullivan JP. A critical review of consumer wearables, mobile applications, and equipment for providing biofeedback, monitoring stress, and sleep in physically active populations. Front Physiol 9: 743, 2018.

56. Pérez-Castilla A, Piepoli A, Delgado-García G, Garrido-Blanca G, García-Ramos A. Reliability and concurrent validity of seven commercially available devices for the assessment of movement velocity at different intensities during the bench press. J Strength Cond Res 33(5): 1258-1265, 2019.

57. Prochaska JJ, Spring B, Nigg CR. Multiple health behavior change research: an introduction and overview. Prev Med 46(3): 181-188, 2008.

58. Rauch TJ, Ugrinowitsch C, Barakat IC, Alvarez RM, Brummert LD, Aube WD, Barsuhn SA, Hayes D, Tricoli V, De Souza OE. Auto-regulated exercise selection training regimen produces small increases in lean body mass and maximal strength adaptations in strength-trained individuals. J Strength Cond Res 34(4): 1133-1140, 2020.

59. Reed DD, Niileksela CR, Kaplan BA. Behavioral economics. Behav Anal Pract 6(1): 34-54, 2013.

60. Reid VL. Clinical investigation of athletes with persistent fatigue and/or recurrent infections. Br J Sports Med 38(1): 42-45, 2004.

61. Rodrigues JAL, Santos BC, Medeiros LH, Gonçalves TCP, Júnior CRB. Effects of different periodization strategies of combined aerobic and strength training on heart rate variability in older women. J Strength Cond Res 35(7): 2033-2039, 2021.

62. Rose EA, Parfitt G. Pleasant for some and unpleasant for others: A protocol analysis of the cognitive factors that influence affective responses to exercise. Int J Behav Nutr Phys Act 7: 15, 2010.

63. Ruegsegger GN, Booth FW. Health benefits of exercise. Cold Spring Harb Perspect Med 8(7): a029694, 2018.

64. Ryan RM, Deci EL. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am Psychol 55(1): 68-78, 2000.

65. Sanchez-Medina L, Gonzalez-Badillo JJ, Perez CE, Pallares JG. Velocity- and power-load relationships of the bench pull vs. Bench press exercises. Int J Sports Med 35(3): 209-216, 2014.

66. Sarzynski MA, Loos RJF, Lucia A, Pérusse L, Roth SM, Wolfarth B, Rankinen T, Bouchard C. Advances in exercise, fitness, and performance genomics in 2015. Med Sci Sports Exerc 48(10): 1906-1916, 2016.

67. Saw AE, Main LC, Gastin PB. Monitoring athletes through self-report: Factors influencing implementation. J Sports Sci Med 14(1): 137-146, 2015.

68. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. Br J Sports Med 50(5): 281-291, 2016.

69. Seshadri DR, Li RT, Voos JE, Rowbottom JR, Alfes CM, Zorman CA, Drummond CK. Wearable sensors for monitoring the physiological and biochemical profile of the athlete. NPJ Digit Med 2: 72, 2019.

70. Shaffer F, Ginsberg JP. An overview of heart rate variability metrics and norms. Front Public Health 5: 258, 2017.

71. Steele J, Endres A, Fisher J, Gentil P, Giessing J. Ability to predict repetitions to momentary failure is not perfectly accurate, though improves with resistance training experience. PeerJ 5: e4105, 2017.

72. Strohacker K, Beaumont CT. The shared criticisms of periodization models and behavior-change theories for exercise: An opportunity for collaborative advancement? Kinesiol Rev 9(2): 170-178, 2020.

73. Strohacker K, Boyer WR, Smitherman KN, Cornelius E, Fazzino D. Assessing energy level as a marker of aerobic exercise readiness: A pilot investigation. Int J Exerc Sci 10(1): 62-75, 2017.

74. Strohacker K, Keegan R, Beaumont CT, Zakrajsek RA. Applying p-technique factor analysis to explore person-specific models of readiness-to-exercise. Front Sports Act Living 3: 685813, 2021.

75. Strohacker K, Sudeck G, Keegan R, Ibrahim AH, Beaumont CT. Contextualising flexible nonlinear periodization as a person-adaptive behavioral model for exercise maintenance. Health Psychol Rev 10: 1-14, 2023.

76. Strohacker K, Zakrajsek RA. Determining dimensionality of exercise readiness using exploratory factor analysis. J Sports Sci Med 15(2): 229-238, 2016.

77. Strohacker K, Zakrajsek RA, Schaltegger ET, Springer CM. Readiness to perform aerobic activity in adults with obesity: A thematic analysis of online surveys. Res Q Exerc Sport 90(4): 619-628, 2019.

78. Summers SJ, Keegan RJ, Flood A, Martin K, McKune A, Rattray B. The acute readiness monitoring scale: Assessing predictive and concurrent validation. Front Psychol 12: 738519, 2021.

79. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, Moher D, Peters MDJ, Horsley T, Weeks L, Hempel S, Akl EA, Chang C, McGowan J, Stewart L, Hartling L, Aldcroft A, Wilson MG, Garritty C, Lewin S, Godfrey CM, Macdonald MT, Langlois EV, Soares-Weiser K, Moriarty J, Clifford T, Tunçalp Ö, Straus SE. Prisma extension for scoping reviews (prisma-scr): Checklist and explanation. Ann Intern Med 169(7): 467-473, 2018.

80. Tversky A, Kahneman D. Judgment under uncertainty: Heuristics and biases. Science 185(4157): 1124-1131, 1974.

81. Walts CT, Murphy SM, Stearne DJ, Rieger RH, Clark KP. Effects of a flexible workout system on performance gains in collegiate athletes. J Strength Cond Res 35(5): 1187-1193, 2021.

82. Weaving D, Jones B, Till K, Abt G, Beggs C. The case for adopting a multivariate approach to optimize training load quantification in team sports. Front Physiol 8: 1024, 2017.

83. Wendel-Vos GCW, Schuit AJ, Tijhuis MAR, Kromhout D. Leisure time physical activity and health-related quality of life: Cross-sectional and longitudinal associations. Qual Life Res 13(3): 667-677, 2004.

