DISSERTATION / DOCTORAL THESIS

Titel der Dissertation /Title of the Doctoral Thesis

„Modeling Strength Endurance:

an Individualized Approach“

verfasst von / submitted by

Benedikt Mitter, Bakk. MSc

angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD)

Wien, 2022 / Vienna 2022

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	UA 794 680 481
Dissertationsgebiet lt. Studienblatt / field of study as it appears on the student record sheet:	Sportwissenschaft / Sports Science
Betreut von / Supervisor:	Ass.-Prof. Mag. Dr. Harald Tschan

Acknowledgments

The present doctoral thesis could not have been completed without the support of several people. Therefore, I would like to express my sincere gratitude to everyone who contributed along the way, whether in the form of technical advice, voluntary participation in experiments, assistance during data acquisition, or simply mental and social support.

First and foremost, I would like to acknowledge my supervisor, Ass.-Prof. Mag. Dr. **Harald Tschan**. You supported me long before my actual PhD journey began by offering me the opportunity to join your department as a teaching assistant and, consequently, learn from a group of brilliant individuals. You allowed me to pursue my scientific vision for practice-oriented research ever since and provided help whenever it was needed. I'm glad to consider you not only a great supervisor but also a friend. Thank you!

I would like to thank my superior and current head of the department of Training Science at the Centre for Sport Science and University Sports in Vienna, Univ.-Prof. Mag. Dr. **Robert Csapo**. You not only shared your knowledge and provided valuable input for the final two papers emanating from my PhD project but also supplied me with all the resources required to complete this thesis. Your vision for the department is genuinely sensational, and it is without a doubt that you will help to bring forth many bright minds who will contribute to valuable scientific discoveries. Thank you!

I would also like to thank my close friend, Mag. Dr. **Pascal Bauer**, Bakk., for every piece of support over the past years. You encouraged me to pursue the academic path. You helped me out as a colleague and a friend, even when I felt like losing the ground underneath my feet. You sheltered me without hesitation when I had nowhere else to go. Indubitably, I would not be where I am right now if it wasn't for you. Thank you for your expertise! Thank you for your friendship! Thank you for everything!

In addition, I want to explicitly thank my mentor in Bayesian modeling, Dr. rer. biol. hum. **Lei Zhang**, MSc. You shared your expertise countless times and familiarized me with the Bayesian framework, Stan coding, and technical jargon. You provided ideal sources and references for every arising question and mediated the most valuable skills I developed over the course of my PhD. I dare to say with certainty that the papers resulting from this dissertation project would not have inherited the analytical quality presented if it was not for your technical guidance. Thank you!

This doctoral thesis could not have been completed without the help of several more of my dear colleagues, to whom I would like to collectively express my gratitude. Most notably, I would like to thank **Peter Raidl**, Bakk. BSc MSc, and Univ.-Prof. Dipl.-Ing. Dr. **Arnold Baca** for contributing substantially to parts of the project. I'd also like to thank **Marie-Therese**

Plass, BSc, for helping out with pilot tests in the early stages of the project, and **Gustavo Zaccaria Schaun**, BSc PhD, for completing language editing on this thesis.

Likewise, I would like to acknowledge all those who actively participated in the experiments that gave rise to this thesis, despite all complications that came along with the pandemic starting 2020. The project could not have been realized without your effort. I feel honored to be given a chance to work with such dedicated athletes. Thank you!

Finally, I would like to thank my love, **Verena Schweng**. You have supported my work both mentally and socially ever since we met. You encouraged me to pursue my vision. You provided balance to my life and taught me to cherish every experience. I owe you so much more than I could ever express in words. Thank you for the life we share! I love you!

This thesis is dedicated to my parents.

Table of Contents

Abstract

The relationship between the applied load and the number of repetitions performed to momentary failure (i.e., the strength-endurance relationship) in a given exercise has repeatedly drawn the interest of researchers over the past decades. While this relationship was commonly assumed to be virtually identical across individuals and, thus, described by unified equations, there is evidence that it may actually differ between individuals. The present thesis aimed to investigate the concept of "strength-endurance profiles", which describe the strength-endurance relationship on an individual level. The main objective was to identify a model function that yields good descriptive and predictive validity while being robust across test-retest trials. Since strength-endurance profiles require the completion of multiple repetitions-to-failure tests, the thesis further aimed to compare different strategies for data acquisition to evaluate whether they may be used interchangeably. Based on the findings, it was concluded that the individual strength-endurance relationship can be best represented by a 2-parameters exponential regression or a reciprocal regression function. Data acquisition should be completed in multiple separate sessions distributed across different days, rather than a single session with 22 min breaks in between repetitions-to-failure tests.

Zusammenfassung

Der Zusammenhang zwischen der bewegten Last und der Anzahl maximal durchführbarer Wiederholungen bis zum Muskelversagen (der Kraft-Ausdauer-Zusammenhang) in einer bestimmten Übung wurde während der letzten Jahrzehnte wiederholt als Thema der sportwissenschaftlichen Forschung aufgegriffen. Während angenommen wurde, dass dieser Zusammenhang für alle Personen annähernd identisch ist und daher durch einheitliche Gleichungen beschrieben werden kann, bestehen Hinweise darauf, dass der Zusammenhang in Wahrheit individuell ausgeprägt ist und somit zwischen Personen variiert. Die Motivation der vorliegenden Dissertation bestand darin, das Konzept von „Kraft-Ausdauer-Profilen" zu erforschen, die den Kraft-Ausdauer-Zusammenhang auf individueller Ebene beschreiben. Das Hauptziel war es, eine Modellfunktion zu identifizieren, die gute deskriptive und prädiktive Eigenschaften aufweist und in der Abwesenheit von systematischen Änderungen der Leistungsfähigkeit robust ist. Da Kraft-Ausdauer-Profile mehrere Tests bis zum Muskelversagen (RTF-Tests) erfordern, zielte die Dissertation außerdem darauf ab, verschiedene Strategien für die Datenerhebung zu vergleichen. Basierend auf den Ergebnissen wurde der Schluss gezogen, dass der individuelle Kraft-Ausdauer-Zusammenhang am besten durch eine 2-Parameter-exponentielle Regression oder eine reziproke Regressionsfunktion

dargestellt werden kann. Die Datenerhebung sollte in mehreren separaten Test- bzw. Trainingseinheiten durchgeführt werden, die über verschiedene Tage verteilt sind, und nicht in einer einzelnen Einheit mit 22-minütigen Pausen zwischen den RTF-Tests.

1 Introduction

1.1 Strength endurance

Strength endurance, which is often used interchangeably with the term "local muscular endurance" (LME), is considered a major training goal and essential physical quality in various sports such as Climbing (Grant et al., 1996), Crossfit® (Gómez-Landero & Frías-Menacho, 2020; Leitão et al., 2021), Rowing (Kramer et al., 1994; Lawton et al., 2011), Strongman (Winwood et al., 2019) and certain combat sports (Chaabene et al., 2017; Santos-Junior & Franchini, 2021). However, the pursuit of understanding strength endurance reaches far beyond sports that assume it to be a determinant of competitive performance. In the general domain of strength and conditioning, current trends suggest that many practitioners aspire to quantify proximity to momentary failure to regulate the intensity of effort applied during resistance training (Hickmott et al., 2022; Pelland et al., 2022). A better comprehension of the strength endurance capacity can facilitate such implementations, as discussed in chapter 1.2.2.2 ("Potential applications of the strength-endurance models"). For a start, the present chapter aims to provide the reader with a comprehensive definition of strength endurance and related terms, introduce the current standards used to assess and quantify strength endurance, and portray potential psycho-physiological causes associated with acute fatigue.

1.1.1 Definition of strength endurance

Various definitions have been proposed to distinguish strength endurance from other physical qualities (Table 1). Generally speaking, strength endurance can be described as the ability to resist neuromuscular fatigue during the execution of a specific exercise or movement against a submaximal resistance (Deschenes & Kraemer, 2002). Within this framework, some authors suggested two additional definitions of strength endurance based on mechanical quantities that apply to specific types of muscle action. Among isometric exercises, strength endurance would then be defined as the ability to maintain a high level of muscular force over time (Verkhoshansky & Siff, 2009). For dynamic exercises, on the other hand, strength endurance would be primarily described as the ability to produce a large amount of concentric work (Lawton et al., 2011; Verkhoshansky & Siff, 2009). In a broader sense, this latter definition would pertain to the ability to realize a maximum amount of physical work within a given time frame or the ability to minimize the time required to produce a given amount of physical work, both of which include strategic aspects of optimizing interposed rest periods. However, throughout this manuscript, strength endurance will be considered in its most basic form as the ability to maintain force production in a single sustained trial, cluster, or set, neglecting recovery processes that would take place between them.

Table 1. Definitions of strength endurance and local muscular endurance

Source	Term	Definition
Deschenes & Kraemer, 2002, p. 3	LME	"[…] *the ability to resist muscular fatigue, particularly when using a submaximal resistance* […]."
Haff & Triplett, 2016, p. 261	LME	"[…] *the ability of certain muscles or muscle groups to perform repeated contractions against a submaximal resistance* […]."
Lawton et al., 2011, pp. 414–415	LME & SE	"[…] *total concentric work produced over a number of repetitions, often within a designated time interval* […]."
Verkhoshansky & Siff, 2009, p. 108	SE	"[…] *the ability to effectively maintain muscular functioning under work conditions of long duration. In sport this refers to the ability to produce a certain minimum force for a prolonged period. There are different types of muscle functioning associated with this ability, such as holding a given position or posture (static strength-endurance), maintaining cyclic work of various intensities (dynamic strength-endurance) or repetitively executing explosive effort (explosive strength-endurance)* […]."
Zatsiorsky & Kraemer, 2006, p. 180	LME & SE	"*The ability to produce multiple muscular contractions at different percentages of maximum* […]."

LME, local muscular endurance; SE, strength endurance.

1.1.2 Assessment of strength endurance

Strength endurance can be expressed through different physical attributes depending on the type of muscle action performed and the available diagnostic technology, leading to various tests proposed in the scientific literature. Amongst them, Milner-Brown et al. (1986) proposed that *muscle endurance* could be quantified based on kinetic assessment in two ways: as the Force-Time Integral (FTI) or as the Fatigue Index (FI). The first can be calculated as the area under the force-time curve for a given time interval and expressed as a factor of body mass (BM):

$$FTI\ [Ns\ kg^{-1}] = BM^{-1} \int F\ dt \tag{1}$$

The second, in turn, can be calculated as the reduction in maximum force produced up to a certain time point (F_i - F_n) relative to the initial maximum force produced (F_i):

$$FI\ [\%] = 100\ \frac{F_i - F_n}{F_i} \tag{2}$$

Milner-Brown et al. (1986) suggested these two variables in the context of isometric exercises, ultimately linking them to the definition of *static strength endurance* formulated by Verkhoshansky and Siff (2009). It follows then that *dynamic strength endurance* could be quantified as the mechanical work (W) produced, which is expressed mathematically as the integral of force over a certain distance (s):

$$W\ [Nm] = \int F\ ds \tag{3}$$

While these approaches relate closely to proposed mechanical definitions of strength endurance, they require access to specific technology for assessing force production. However, such tools are typically unavailable to practitioners. Therefore, research focusing on an audience of applied practitioners commonly resorts to using variables that can be easily assessed without expensive equipment. Such variables constitute approximations of the mechanistic definitions of strength endurance described in the previous section and pertain to specific types of muscle actions.

In isometric exercises like the *front hold* (i.e., holding an external load at shoulder height with extended elbows) or dynamic exercises featuring a constant cadence in a cyclic movement like *tempo squats* (i.e., squats with a prescribed duration for eccentric, concentric, and isometric movement phases), strength endurance may be assessed as the time (t_{lim}) the exercise can be sustained under predetermined conditions (Ansdell et al., 2019; Arakelian et al., 2017). In the two examples mentioned above, such conditions might encompass holding the external load at a certain angle of glenohumeral flexion in the front hold exercise or maintaining a target movement cadence or movement technique in the tempo squat.

In dynamic exercises, strength endurance is typically reflected by the number of repetitions that can be performed before reaching momentary failure (RTF), hence not being able to complete the concentric phase of another repetition without deviating from predetermined conditions (Steele, Fisher, et al., 2017). Such conditions may include the ability to maintain a given movement cadence or the ability to maintain a given exercise technique. In the deadlift, for example, momentary failure could be interpreted as the point at which excessive rounding of the lower back occurs (Dinyer, Byrd, Vesotsky, Succi, & Bergstrom, 2019). In the pull-up, on the other hand, momentary failure could be associated with the inability to complete another repetition across the full range of motion, starting with fully extended elbows and pulling the hyoid bone to the level of the bar or above (LaChance & Hortobagyi, 1994). Importantly, these predetermined criteria would not exclude the possibility that after reaching momentary failure, more repetitions could be performed with an undesirable exercise technique (i.e., a rounded lower back in the deadlift or a reduced range of motion in the pull-up). Assessments of dynamic strength-endurance by RTF (i.e., RTF tests) are typically referred to as repetition maximum tests or repetition endurance tests (Lawton et al., 2011).

The previously described variables are typically determined under standardized conditions to compare strength endurance within and between individuals. In exercises with isoinertial loading (i.e., when exercising against a constant external load), research has promoted two different approaches to standardization: first, the *absolute strength endurance* can be tested against a fixed load, which is predominantly expressed in a unit of mass like kg or lbs (Anderson & Kearney, 1982; Hackett et al., 2022; Johnson et al., 2009; Ratamess et al., 2009; Schoenfeld et al., 2021; M. H. Stone et al., 2006; W. J. Stone & Coulter, 1994). A popular field test for absolute strength endurance is the NFL-225 test, which is commonly applied in the National Football League (NFL) Combine and requires the athlete to perform repetitions to momentary failure in the bench press exercise at a load of 225 lbs or 102.3 kg (Mann et al., 2012; Mayhew et al., 1999). Second, the *relative strength endurance* can be tested against a fixed percentage of a reference load. Typically, relative loads are expressed as a percentage of the individual's one-repetition maximum (1-RM) load or as a percentage of the individual's body mass (Anderson & Kearney, 1982; Hackett et al., 2022; Johnson et al., 2009; Ratamess et al., 2009; Schoenfeld et al., 2021; M. H. Stone et al., 2006; W. J. Stone & Coulter, 1994).

Notably, research has distinguished two methodological strategies when testing relative strength endurance at a given percentage of the 1-RM to evaluate the longitudinal development of strength endurance within an individual over time. On the one hand, the used load could be expressed relative to the pre-intervention 1-RM (1-RM$_{PRE}$) and maintained for subsequent tests. On the other hand, relative loads could be adjusted continuously to any emerging changes on the 1-RM (1-RM$_{POST}$) across the training process (Fisher et al., 2020; Hackett et al., 2022; Schoenfeld et al., 2021). Naturally, the second approach would require an initial 1-RM test before each assessment of relative strength endurance to warrant valid and reliable results.

1.1.3 Fatigue in resistance training

As described in section 1.1.1, strength endurance can be interpreted as the ability to maintain neuromuscular control and muscle function in the presence of accumulated exercise-induced fatigue. Thus, understanding causal psycho-physiological pathways and biomechanical consequences of fatigue during sustained resistive exercise and how they affect neuromuscular control and muscle function may help explain certain systemic phenomena outlined in the present manuscript. For that reason, the following section will provide the reader with a brief summary of the current knowledge concerning neuromuscular fatigue in resistance training.

1.1.3.1 Definitions of fatigue and exhaustion

Exercise-induced fatigue is typically described as a reversible loss of maximal muscular performance (i.e., force- or power-generating capacity) during prolonged physical tasks (Allen et al., 2008; Armes et al., 2020; Enoka & Duchateau, 2008; Finsterer, 2012; Gandevia, 2001; Halperin et al., 2021; Meeusen et al., 2006; Piqueras-Sanchiz et al., 2021; Westerblad et al., 2002). Notably, MacIntosh and Rassier (2002) criticized this established definition of fatigue because it did not account for the phenomenon of *low-* and *high-frequency fatigue*, according to which contractile function can be diminished selectively at specific stimulation frequencies. The authors proposed an alternative definition, describing fatigue as "[…] *a response that is less than the expected or anticipated contractile response, for a given stimulation* […]" (MacIntosh & Rassier, 2002, p. 44). Therefore, exercise-induced fatigue can be generalized as a reversible loss of contractile function resulting from physical activity.

Based on this last definition, exercise-induced fatigue differs conceptually from muscle damage (syn., muscle injury), which also results in a loss of contractile function, but typically requires longer periods of recovery to be restored (Allen et al., 2008; Finsterer, 2012). However, it is challenging to differentiate between fatigue and muscle damage solely based on the time course of impaired muscle function since there have also been reports of a slowly reversible component of fatigue (Edwards et al., 1977). Rather, fatigue and muscle damage can be better distinguished based on their effect on myofibrillar structures. Specifically, muscle damage is linked to structural alterations, including sarcomere disorder and membrane disruption, which are not necessarily present in a fatigued condition (Allen et al., 2008). Furthermore, muscle damage may occur without physical activity due to other traumatic events, such as contusions (Finsterer, 2012).

Exhaustion represents another term that is commonly used in association with fatigue, and therefore requires a clear definition and substantial distinction. Allen and colleagues (2008) proposed that exhaustion should be interpreted as the "[…] *failure to be able to continue the activity at the original intensity* […]" (p. 288). Therefore, the term may be understood synonymously with *task failure* or *momentary failure*, which marks a distinct point during a continuous or repetitive exercise bout, whereas fatigue describes a continuous process (Cairns et al., 2005; Steele, Fisher, et al., 2017).

1.1.3.2 Classification of fatigue

Scientific literature usually proposes two categorizations of exercise-induced fatigue. The first categorization distinguishes fatigue according to the affected frequency of innervation or stimulation (i.e., *low-* vs. *high-frequency fatigue*). The second, in turn, determines fatigue according to its causal origin in the neuromuscular system (i.e., *central* vs. *peripheral fatigue*).

MacIntosh and Rassier (2002) described low-frequency fatigue (LFF) as a physiological state where "[…] *the contractile response to low frequency stimulation is diminished while at the same time, the response to high frequency stimulation is not affected* […]" (p. 44). Importantly, LFF is not exclusively associated with fatiguing activities performed at low motor unit discharge rates but has been reported to result from various stimulation frequencies ranging from 10 to 100 Hz (Keeton & Binder-Macleod, 2006). To avoid misinterpretation, Allen et al. (2008) proposed the alternative term *prolonged low-frequency force depression*. Indeed, LFF is typically characterized by a slower recovery process, taking several hours or even days to fully recover (Edwards et al., 1977). On the other hand, high-frequency fatigue (HFF) has been defined as a pronounced loss of force at high stimulation frequencies (Allen et al., 2008). According to Jones (1996), HFF is characterized by a reduced amplitude and a slower waveform of the muscle fiber action potential, which can be rapidly restored once the muscle stimulation frequency is reduced below a certain threshold. However, the authors question whether HFF contributes to conventional mechanisms of exercise-induced fatigue since voluntary contractions are believed to plateau at a motor unit firing rate of around 30 Hz. In contrast, HFF has been predominantly reported in response to evoked contractions at much higher frequencies. Furthermore, sustained voluntary contractions have been shown to only minimally affect the waveform of action potentials (Jones, 1996).

Exercise-induced fatigue has also been commonly classified according to where its causal processes originate. Typically, literature applies the category of central fatigue to processes leading to an impairment in the neural drive on the spinal or supraspinal (cerebral) level, while peripheral fatigue is used to describe cellular mechanisms distal to the neuromuscular junction (Gandevia, 2001; Kataoka et al., 2022; Meeusen et al., 2006). Therefore, peripheral fatigue is not considered to be associated with voluntary muscle activation (Gandevia, 2001) but rather with the depletion of high-energy substrates, the accumulation of metabolites, or a combination of both (Kataoka et al., 2022). However, as outlined by numerous authors, central and peripheral fatigue typically coexist (Nybo & Secher, 2004; Ruotsalainen et al., 2014; Thomas et al., 2018) and may mutually affect one another (Meeusen et al., 2006).

For example, it has been suggested that during peripheral fatigue processes, certain metabolic products may stimulate receptors innervated by group III and IV nerve afferents and, consequently, affect central motor drive (Barry & Enoka, 2007; Davis & Bailey, 1997; Enoka & Duchateau, 2008; Gandevia, 2001; Laurin et al., 2015; Westerblad et al., 2002; Zając et al., 2015).

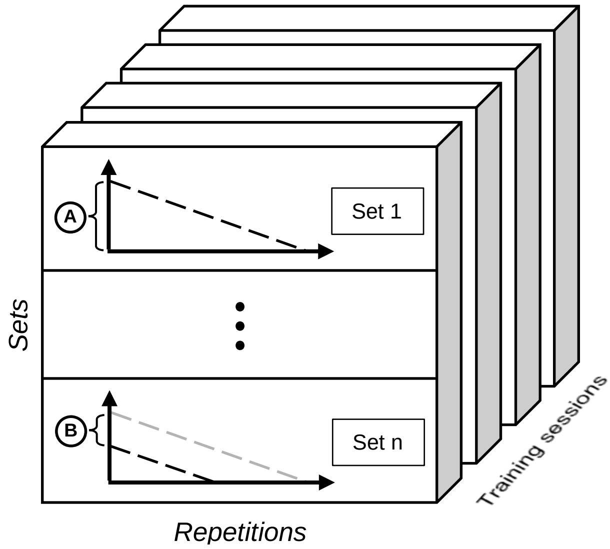

Figure 1. Dimensions of exercise-induced fatigue. Y-axes of line graphs display performance as an unspecified arbitrary variable. Fatigue development was simplified as a linearly decreasing trend (black dashed lines). For reference, the grey dashed line represents fatigue development in set 1, performed under fully rested conditions. A, intra-set fatigue; B, inter-set fatigue.

While the categorizations mentioned above focus on physiological mechanisms, some authors have also considered a more phenomenological approach to classify fatigue based on its occurrence within the structure of a resistance training program (Figure 1). This classification distinguishes between *intra-set fatigue* and *inter-set fatigue*. Carneiro et al. (2020) described intra-set fatigue as the "[…] *acute decline of technical proficiency and of movement force and velocity from first to last repetition* […]" during a training set (p. 239.e2). Therefore, it defines decrements of performance (e.g., movement velocity, power output) in a single sustained or repetitive trial, excluding regenerative processes that may occur during interposed rest periods between trials. Consequently, intra-set fatigue is causally associated with momentary failure. Inter-set fatigue, on the other hand, could be described as a loss in performance happening across a multitude of sets or trials, which can be expressed under standardized conditions as the reduced ability to maintain high levels of maximum voluntary movement velocity or mechanical power (Fonseca et al., 2020; Morán-Navarro et al., 2017; Pareja-Blanco et al., 2019; Pareja-Blanco, Rodríguez-Rosell, et al., 2020; Párraga-Montilla et al., 2020; Piqueras-Sanchiz et al., 2021; Sánchez-Medina & González-Badillo, 2011), the reduced ability to produce high levels of force (Piqueras-Sanchiz et al., 2021), or as the reduced capacity to perform physical work (Salles et al., 2009) during subsequent sets. Compared to intra-set fatigue, inter-set fatigue may depend on additional factors, such as total training volume, rest duration between sets, and recovery rates (Salles et al., 2009). Importantly, intra-set and inter-set fatigue may arise at different magnitudes during the same training session. However, evidence supports a causal relationship, where higher levels of intra-set fatigue promote higher levels of inter-set fatigue during subsequent sets (Gorostiaga et al., 2012; Gorostiaga et al., 2014).

1.1.3.3 Peripheral and central mechanisms of fatigue

The initiation and regulation of voluntary human movement are considered complex procedures of processing and transmitting signals between different physiological systems. They include the central nervous system (i.e., cerebral cortex, thalamus, basal ganglia, cerebellum, brain stem, spinal cord), the peripheral motoneuron, the neuromuscular junction, sarcolemma, t-tubules, sarcoplasmic reticulum, and the cross-bridge cycle of myofilaments (Figure 2). It has been suggested that fatigue could be caused at any point along this pathway, with peripheral and central mechanisms affecting four main processes in the signal chain. First, fatigue mechanisms could affect the targeted recruitment of motor units. Second, they could affect the discharge rate of motor units by interfering with the propagation of action potentials in the central and peripheral nervous system and along the sarcolemma. Third, they could impede excitation-contraction coupling by compromising cytoplasmic calcium (Ca^{2+}) concentration or reducing myofibrillar Ca^{2+} sensitivity, both of which are considered crucial since Ca^{2+} binding to troponin C facilitates the cross-bridge cycling of myosin on actin. Fourth, fatiguing mechanisms could directly affect force production at the cross-bridge level.

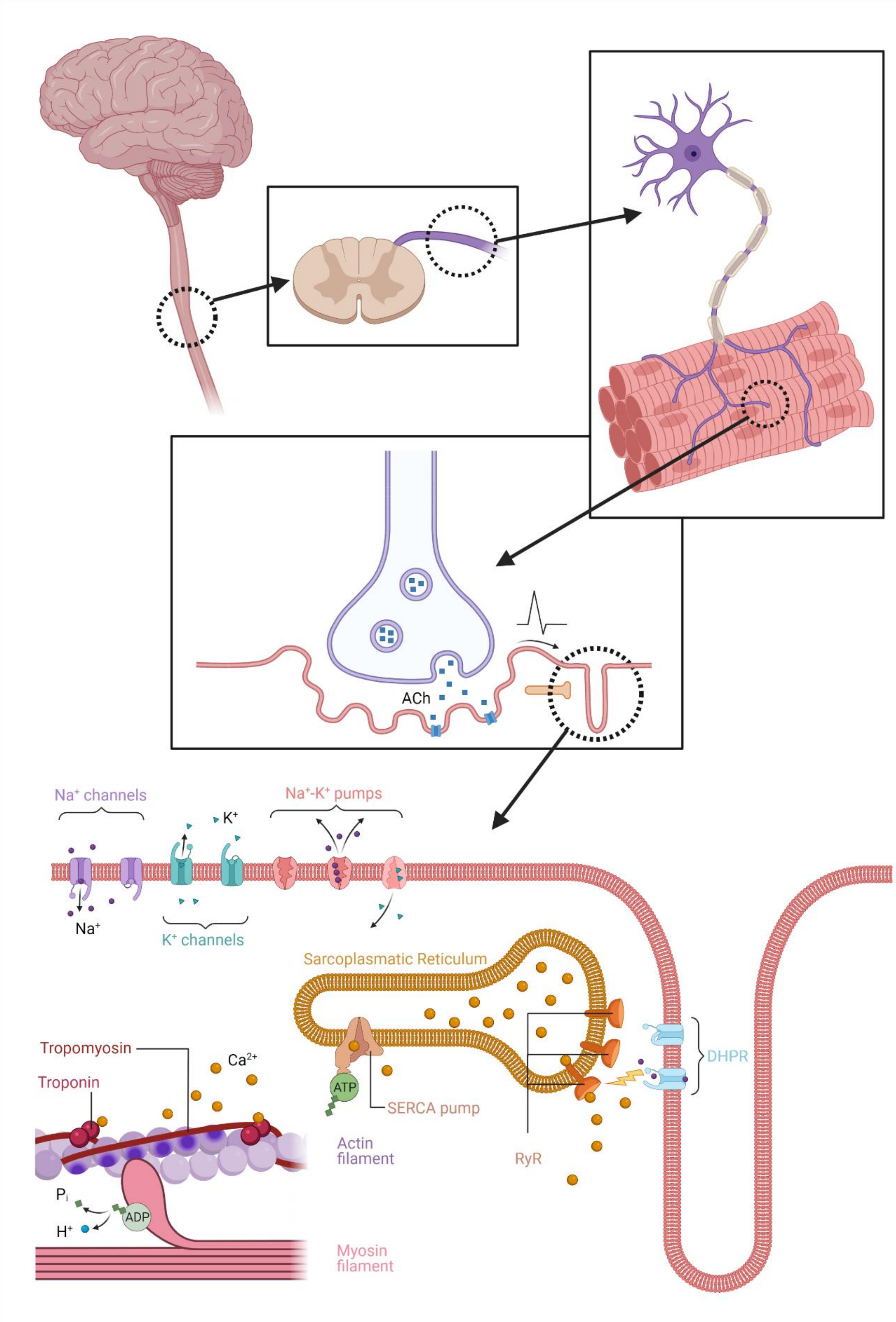

Figure 2. Schematic summary of physiological systems involved in voluntary skeletal muscle contraction and fatigue.

Adapted from "Cross-bridge Cycle" by BioRender.com (2022). Retrieved from https://app.biorender.com/biorender-templates.

Exercise-induced fatigue is likely the result of multiple effects emerging simultaneously or in overlapping series (Allen et al., 2008). The objective of the following section will be to provide an overview of proposed biological mechanisms causing intra-set fatigue and, therefore, influence strength endurance.

Peripheral mechanisms: depletion theory

Energy metabolism in resistance training

Many cellular processes which are associated with muscle contraction, such as cross-bridge cycling or control of intracellular Ca^{2+} concentration, require adenosine triphosphate (ATP) as a source of energy (Allen et al., 2008). This energy is stored within the ATP molecule in the form of binding energy and can be released through the decomposition (i.e., hydrolysis) of ATP into adenosine diphosphate (ADP) and an inorganic phosphate ion (P_i or PO_4^{3-}), using ATPase enzymes as a catalyst (Fitts, 1994):

$$ATP + H_2O \rightarrow ADP + P_i + H^+ + energy \quad (4)$$

During muscular activity, a permanent demand for energy must be met, which increases with the intensity and duration of the activity. This demand requires ATP to be continuously resynthesized to balance ATP utilization. While, in general, ATP can be produced from various metabolic processes under aerobic and anaerobic conditions, resistance training energy demand is typically fueled by the anaerobic energy metabolism (C. B. Scott et al., 2011; Vianna et al., 2011). This hypothesis is supported by research showing that muscles tend to perform under hypoxic conditions during resistance exercise, especially when dynamic exercises are completed with prolonged continuous muscular tension (Tanimoto & Ishii, 2006; Zając et al., 2015).

Initially, the anaerobic resynthesis of ATP is accomplished by the conversion of phosphocreatine (PCr) and ADP to ATP by the enzyme creatine kinase (Fitts, 1994):

$$PCr + ADP + H^+ \rightarrow Cr + ATP \quad (5)$$

As the resistance exercise bout continues, the recovery of ATP through PCr is progressively supported by processes using other high-energy substrates, most notably anaerobic glycolysis (Bandy et al., 1990). Anaerobic glycolysis is a multi-step process and is therefore considered to contribute to the resynthesis of ATP at a substantially lower rate compared to PCr (Sahlin, 2014). The reaction can be summarized using the following equation (Brooks et al., 2005):

$$Glucose + 2\ ADP + 2\ P_i \rightarrow 2\ ATP + 2\ Lactate + 2\ H^+ \quad (6)$$

Due to ADP being phosphorylated with the help of PCr and Glycogen, ATP levels remain relatively stable during the primary phase of high-intensity muscular activity. At the same time, a reduction in PCr levels and a rise in free creatine (Cr) and P_i can be experienced (Gorostiaga et al., 2010; Gorostiaga et al., 2012; Jones et al., 2009). Once PCr reaches a certain lower threshold, ATP concentration eventually starts to fall, resulting in a rise in ADP concentration, as suggested by eq. 4 (Allen et al., 2008). This increase in ADP facilitates another dephosphorylation process, which converts two ADP molecules into one ATP and one adenosine monophosphate (AMP) molecule by the enzyme adenylate kinase (Fitts, 1994):

$$2ADP \rightarrow AMP + ATP \tag{7}$$

AMP can then be deaminated into inosine monophosphate (IMP) and ammonia (NH_3) by the enzyme AMP deaminase:

$$AMP \rightarrow IMP + NH_3 \tag{8}$$

This final step in the adenine nucleotide metabolism is thought to facilitate energy supply by keeping the ATP:ADP ratio constant and, hence, maintaining the phosphorylation potential elevated (Sahlin & Broberg, 1990). As a consequence, the rate of ADP consumption by anaerobic glycolysis would be reduced, delaying the acidosis of active muscles (Korzeniewski, 2006).

Adenosine Triphosphate

While a cumulative loss of locally available ATP could be considered a straightforward explanation for fatigue, the causal role of lowered ATP resynthesis rates is still under debate. According to Allen et al. (2008), cytoplasmic ATP concentration does not drop below ~60% of its resting level during stimulated contractions or voluntary exercise. Furthermore, it has been suggested that muscles stimulated at a constant frequency may experience a loss in force without any accompanying changes in ATP levels (Jones et al., 2009). Likewise, Gorostiaga et al. (2010) did not find significant changes in adenine nucleotide concentrations following a 10-RM set in the leg press. However, significant reductions in ATP have been reported when performing three sets at 10-RM separated by 2 min of rest (Gorostiaga et al., 2012) or after three sets of 30 repetitions at $180° \cdot s^{-1}$ using an isokinetic dynamometer (Jansson et al., 1987). Similar effects have been reported for the knee extension exercise performed to failure, with exercise duration ranging from roughly 2 to 5 min (Gorostiaga et al., 2012). Therefore, it is possible that the depletion of ATP may be a limiting factor throughout multiple sustained efforts or when higher training volumes are performed close to momentary failure. However, the same may not necessarily be valid during the performance of single sets at high loads.

Creatine phosphate

Decreased PCr availability may contribute to the development of fatigue during high-intensity resistance exercise, given that it provides a higher rate of ATP supply compared to anaerobic glycolysis (Sahlin, 2014). However, similar to ATP, PCr is not entirely depleted after single sets performed to failure. For instance, MacDougall et al. (1999) investigated changes in PCr concentration from biopsies of the biceps brachii muscle following either one or three sets of arm curls performed to failure at 80% 1-RM and interposed with 3-min rest intervals. The authors reported a 62% and 50% decrease in PCr concentration compared to pre-exercise conditions, respectively. Similarly, Gorostiaga et al. (2010) found that PCr concentration was reduced to 38% of its resting level in the vastus lateralis following ten repetitions in the leg press performed at the previously determined 10-RM load. PCr concentration dropped even further, to about 15% of its resting level, after performing five sets of ten repetitions at the 10-RM load (Gorostiaga et al., 2012). Taken together, the evidence discussed so far suggests that intra-set fatigue is not mediated by the depletion of ATP and, hence, not impacted by changes in ATP resynthesis rates using PCr. Notwithstanding this, caution should be taken as several methodological limitations could potentially bias these findings. Such limitations include, for example, the elapsed time between exercise termination and freezing of the biopsy tissue samples. Despite authors reporting these time intervals to be relatively short [e.g., 5-10 s in Gorostiaga et al. (2010) or 17 ± 5 s in MacDougall et al. (1999)], they give room for high-rate metabolic processes that could potentially confound measurements. Furthermore, creatine phosphate may also contribute indirectly to exercise-induced fatigue through another mechanism that will be addressed in the section on *inorganic phosphate*.

Glycogen

The contribution of glycogen to ATP resynthesis increases with the duration of muscular activity and, therefore, as the number of repetitions performed increases (Sahlin, 2014). Indeed, research has shown that intramuscular glycogen is significantly depleted over the course of multiple consecutive sets performed to failure (Hokken et al., 2021; MacDougall et al., 1999; R. W. Morton et al., 2019; Pascoe et al., 1993; Roy & Tarnopolsky, 1998; Wilburn et al., 2020). However, MacDougall et al. (1999) noted that after a single set of arm curls performed to failure at 80% 1-RM, there was only a non-significant 12% decrease in intramuscular glycogen. Thus, available evidence suggests that intra-set fatigue is likely not limited by glycogen depletion at higher loads. While it cannot be excluded that glycogen availability may play a role in sets performed to failure at very light loads, it may not be easy to causally attribute any potential effects to glycogen depletion *per se*. These effects might also be explained by the accumulation of specific metabolites formed during anaerobic glycolysis, which will be addressed in the following sections.

Peripheral mechanisms: accumulation theory

Potassium

Potassium (K^+) plays an essential role in the regulation of membrane potential in combination with other ions, most importantly Sodium (Na^+) and Chloride (Cl^-). During muscle excitation, the efflux of K^+ into the extracellular space repolarizes the cell after voltage-gated ion channels cause depolarization through the facilitation of Na^+ influx, allowing action potentials to be propagated along neurons, the sarcolemma, and t-tubules. Research has shown that during repeated stimulation of muscles, extracellular K^+ increases substantially, particularly in the t-tubules of muscle cells. Allen et al. (2008) suggested that this may be due to inadequate compensation by Na^+-K^+ pumps and might potentially reduce muscle excitability during prolonged physical activity. The authors' theory is supported by studies showing a decrease in M-wave amplitude following a local fatiguing protocol (Froyd et al., 2018; Stutzig & Siebert, 2017). Nevertheless, many studies also reported that declines in force or twitch response related to exercise-induced fatigue were not accompanied by a systematically decreased M-wave. These results suggest that muscle excitability at the sarcolemma might not contribute to fatigue-related changes in performance (Baker et al., 1993; Bigland-Ritchie, Cafarelli, & Vøllestad, 1986; Bigland-Ritchie, Furbush, & Woods, 1986; Rozand et al., 2015; Souron et al., 2020; West et al., 1996). The lack of consensus in the literature may be partially attributed to methodological differences among studies, which cause heterogeneity in certain factors that have been reported to influence the magnitude of recorded fatigue. Such factors include the delay between exercise termination and assessment of neuromuscular function, the intensity of stimulation, and the analytical method used to quantify fatigue (Place & Millet, 2020).

It should also be noted that fatiguing protocols typically involve repeated submaximal activation bouts with short interposed rest periods. This methodological approach may affect recorded fatigue to some degree, as Allen et al. (2008) proposed that excitation failure is most likely to occur during continuous, high-frequency stimulation. Moreover, the elevated extracellular K^+ concentration during fatigue might also affect performance through pathways other than muscle excitability. For example, Lindinger and Cairns (2021) suggested that elevated K^+ levels might stimulate receptors associated with group III and IV muscle afferents. This stimulation, in turn, could elevate the sensation of pain and the perceived effort, thus potentially contributing to central fatigue processes. Based on the available evidence, the role of K^+ during intra-set fatigue remains unclear. Further research is required on sustained high-intensity exercise bouts to clarify the role of K^+ and muscle excitability during acute fatigue or neuromuscular exhaustion.

Inorganic phosphate

The accumulation of inorganic phosphate (P_i or PO_4^{3-}) is the net result of an increase in ATP hydrolysis and resynthesis through PCr (as portrayed in eq. 4 and eq. 5). While the resynthesis of ATP involving processes such as anaerobic glycolysis (eq. 6) may utilize free P_i to some degree, prolonged exercise is typically characterized by a continuous increase in P_i (Baker et al., 1993; Gorostiaga et al., 2010; Jones et al., 2009; Sinoway et al., 1992). It has been suggested that increased P_i levels may affect muscle contractile properties through various pathways. First, a direct effect on cross-bridge force production has been assumed. This could explain the decrease in evoked tetanic force observed during the initial phase of fatigue when myofibrillar Ca^{2+} levels still increase in response to neural activation or stimulation. Second, P_i may negatively affect myofibrillar Ca^{2+} sensitivity and, therefore, contribute to later phases of fatigue, when the loss in tetanic force is typically accompanied by a decreased Ca^{2+} level. Third, P_i may enter the sarcoplasmic reticulum, potentially leading to the precipitation of calcium phosphate (Ca^{2+}-P_i) as a consequence of exceeding the Ca^{2+}-P_i solubility product, reducing the amount of free Ca^{2+} that could be released into the cytoplasm (Allen et al., 2008; Fitts, 2008; Westerblad et al., 2010). Despite the evidence pointing to a role of P_i in fatigue, the extent to which P_i contributes to exercise-induced fatigue *in vivo* is still not well understood. In fact, most of the previously mentioned mechanisms have predominantly been investigated at unphysiologically low temperatures. In addition, evidence hints towards temperature being a substantial confounding factor to the inhibitory effects of P_i, with less inhibition being present at 30°C compared to 15°C (Debold et al., 2004). Thus, the role of P_i remains unclear in the context of intra-set fatigue in resistance training.

Hydrogen

An increase in intracellular hydrogen (H^+) concentration can result from different metabolic processes that occur during sustained or repeated muscular contractions, most notably the hydrolysis of ATP (eq. 4) and its dissociation from lactic acid (La) during anaerobic glycolysis (eq. 6). A rise in H^+ is associated with a decreased intramuscular pH level and is thought to negatively affect the rate of ATP hydrolysis since ATPase activity responds sensitive to decreases in pH (Keyser, 2010). As a result, a rise in H^+ hinders cross-bridge cycling and the activity of ATP-dependent Na^+-K^+ pumps and Ca^{2+} pumps, leading to reduced contraction force. Furthermore, it has been suggested that low pH levels could have a detrimental effect on the contractile apparatus of skeletal muscle (Fabiato & Fabiato, 1978; Westerblad & Allen, 1993). This effect, however, is considered to be of less relevance to fatigue mechanisms, given the reduced Ca^{2+} pump activity attributed to low pH levels, which helps to maintain a high myofibrillar Ca^{2+} concentration (Wolosker et al., 1997). Overall, an acidic environment favors high levels of free Ca^{2+} in the cytoplasm (Westerblad & Allen, 1993). Indeed, evidence suggests that under physiological temperatures, low pH levels are likely less inhibitory to muscle function than previously assumed and might actually potentiate force development under certain conditions (Allen et al., 2008; Westerblad et al., 2002).

Low pH levels have also been suggested to contribute to fatigue through central processes. Previously, Westerblad et al. (2002) proposed that extracellular acidosis may stimulate receptors innervating group III and IV nerve afferents, which may partially increase the sensation of discomfort during exercise-induced fatigue. Group III and IV nerve afferents have also been reported to regulate central motor drive through spinal and supraspinal mechanisms, which affect voluntary muscle activation (Laurin et al., 2015).

Notably, resistance training has been suggested to cause adaptations in processes responsible for regulating H^+ concentration. Sinoway et al. (1992) reported that bodybuilders experienced a significantly lower reduction in intramuscular pH levels compared to “normal” participants with lower muscle volume and maximum voluntary contraction (MVC) strength following a standardized fatiguing protocol. However, since the authors’ experimental design did not account for actual training-induced changes in fatiguability, these conclusions should be taken with caution.

Ammonia

As described in eq. 8, ammonia (NH_3) is a product of the deamination of AMP. However, NH_3 can also result from the deamination of branched-chain amino acids (BCAA), primarily during reduced glycogen availability, hyperthermia, and ingestion of BCAA (Meeusen et al., 2006). Increases in plasma NH_3 concentrations have typically been associated with high-intensity exercise, hypoxic conditions, and low glycogen levels (Sahlin & Broberg, 1990). In resistance training, there is evidence that plasma NH_3 may rise with increased volume and proximity to voluntary failure, ultimately linking it to fatigue (Gorostiaga et al., 2014; Sánchez-Medina & González-Badillo, 2011). However, the causal pathways between NH_3 and exercise-induced fatigue are not yet fully understood. It has been suggested that since NH_3 can cross the blood-brain barrier, it could potentially affect the cerebral function and, as a result, induce central fatigue. Indeed, hyperammonemia has been reported to impair cerebral blood flow, brain energy metabolism, astrocyte function, synaptic transmission, and the regulation of neurotransmitters (Felipo & Butterworth, 2002). Nevertheless, the cerebral influx of NH_3 originating from active muscle fibers would require sustained blood circulation to allow NH_3 to be "washed out" of active muscles. Yet, research suggests that the performance of high-intensity contractions may impair local circulation above a certain magnitude of intramuscular pressure (Barnes, 1980; Sadamoto et al., 1983; Sejersted et al., 1984; Zwarts & Arendt-Nielsen, 1988). Thus, the causal effect of NH_3 originating from active muscles on the acute fatigue observed during a single sustained high-intensity effort is questionable, whereas NH_3 may contribute to the accumulated fatigue resulting from the repetition of high-intensity efforts (e.g., multiple sets performed with interposed rest periods). For example, Graham et al. (1990) reported a significant rise in plasma NH_3 during sustained knee extensions to exhaustion, which further increased over the first few minutes after exercise cessation and returned to resting levels after 20-30 min. Therefore, it could be assumed that NH_3 may progressively accumulate during a typical resistance training session when sets are performed close to momentary failure.

Reactive Oxygen Species

Reactive oxygen species (ROS) are unstable molecules and ions that contain oxygen, such as superoxide anions ($O_2^{\bullet -}$), hydrogen peroxide (H_2O_2), and hydroxyl radicals ($OH^{\bullet}$). Since they contain an unpaired electron, ROS are highly reactive and facilitate oxidative reactions, predominantly with proteins, lipids, and DNA, leading to oxidative stress and muscle damage (Nikolaidis et al., 2008; Steinbacher & Eckl, 2015). Indeed, ROS are considered to result from various reactions, all of which may be facilitated during strenuous muscular contractions and at increased temperatures (Allen et al., 2008). In experimental research, they have commonly been associated with exercise-induced fatigue. For example, ROS scavengers, such as N-acetyl-cysteine (NAC), have repeatedly been shown to delay or reverse fatigue effects in vitro and in vivo (Allen et al., 2008; Ismaeel et al., 2019; Reid, 2016).

Moreover, it has been suggested that ROS may inhibit Ca^{2+}-activated force production, decrease Ca^{2+} sensitivity, and compromise sarcoplasmic reticulum Ca^{2+} pumping activity within muscle cells. Importantly, these effects have been primarily documented in response to longer exposures to ROS, which do not reflect the typical time scale of a single set in resistance training (Allen et al., 2008; Reid et al., 1993). It should also be noted that oxidative stress markers commonly display a delayed response to strenuous exercise by several hours or even days (Nikolaidis et al., 2008).

Unfortunately, experimental research on oxidative stress in resistance training has not investigated the effects of single sets yet, but rather focused changes over entire training sessions or exercise complexes. For example, Bloomer et al. (2006) found no significant increases in plasma protein carbonyl or malondialdehyde levels after about six sets of squats performed to momentary failure at 70% 1-RM. In contrast, Goldfarb et al. (2008) identified systematic changes in blood protein carbonyls and glutathione levels following three sets of biceps curls and calf extensions performed to failure at 70% 1-RM. Moreover, Deminice et al. (2010) found significant increases in three of six oxidative stress biomarkers following a resistance training session involving six exercises performed for three sets of ten repetitions at 75% 1-RM. Due to the lack of research investigating the acute effects of single sets on ROS accumulation and associated fatigue effects *in vivo*, it is difficult to evaluate whether ROS may influence exercise-induced intra-set fatigue and account for heterogeneity in strength endurance. Based on the results discussed so far, ROS might play a minor role during intra-set fatigue in resistance training. However, ROS may be a substantial factor influencing inter-set fatigue mechanisms during and across entire exercise sessions.

Central mechanisms

Compared to peripheral fatigue, central mechanisms are predominantly subjected to systemic rather than molecular explanations. Overall, the main mechanisms considered responsible for central fatigue are the inhibition of motoneuron excitability and the reduction in (voluntary) corticospinal impulses, which lead to a decreased number of recruited motor units and a decrease in motoneuron firing rate (Davis & Bailey, 1997; Gandevia, 2001). As previously described, the inhibition of motoneuron excitability has been associated with feedback from group III and IV nerve afferents (see sections “Potassium” and “Hydrogen”), which are activated based on the muscle’s mechanical condition and its metabolic environment (Barry & Enoka, 2007; Enoka & Duchateau, 2008; Gandevia, 2001; Laurin et al., 2015; Zając et al., 2015). In turn, the decrease in corticospinal impulses has been attributed to multiple potential mechanisms. First, it could be explained from a psychological perspective by an unwillingness to exert or maintain high levels of physical effort due to perceived discomfort or other motivational reasons (Davis & Bailey, 1997; Gandevia, 2001; Nybo & Secher, 2004; Souron et al., 2020). Second, it may be related to alterations in the interaction of cerebral neurotransmitter systems involving serotonin, catecholamines, glutamate, gamma-aminobutyric acid, and acetylcholine, some of which could be affected by the cerebral influx of NH_3 (Davis & Bailey, 1997; Meeusen et al., 2006; Roelands & Meeusen, 2010).

Corticospinal excitability, sometimes also described as corticospinal responsiveness, is typically assessed using transcranial magnetic stimulation (TMS) to elicit involuntary contractions. Multiple experimental investigations have demonstrated altered corticospinal excitability as a consequence of fatiguing exercise. Latella et al. (2016) found significant reductions in the amplitude of motor-evoked potentials (MEP) following five sets of three repetitions at the 3-RM load in the single-arm dumbbell curl. Similarly, Ruotsalainen et al. (2014) reported significant decreases in the normalized MEP area over the course of three sets of elbow flexions involving eight repetitions performed at an approximate 8-RM load, each set being immediately followed by five isokinetic MVCs. The authors also noted a significant increase in MEP area after the first set compared to the control condition, which did not conform to the observed fatigue-induced reduction in mean isometric MVC force.

Contrary to the abovementioned studies, some experimental interventions did not identify significant changes in corticospinal excitability after fatiguing exercise bouts. For example, Prasartwuth et al. (2005) did not find systematic changes in the MEP area following ten sets of five repetitions in the eccentric elbow flexion performed at 30% of the predicted maximum eccentric force. Thomas et al. (2018) did not find significant changes in the normalized MEP amplitude across a broader spectrum of submaximal TMS intensities after ten sets of five repetitions on the back squats performed at 80% 1-RM, despite results showing a slight (non-significant) trend towards higher values at higher stimulation intensities. These heterogeneous findings reported for corticospinal excitability following fatiguing protocols may partially be explained by methodological differences between studies, such as contraction mode (i.e., eccentric or concentric fatiguing protocols) and TMS settings, including stimulation frequency. Across the discussed studies, no clear trend could be identified for corticospinal excitability after fatiguing exercise.

Decreases in voluntary activation, which are most commonly determined by the twitch interpolation technique using either motor nerve stimulation (VA_{MNS}) or transcranial magnetic stimulation (VA_{TMS}) during MVCs (Shield & Zhou, 2004), have been reported to occur after fatiguing exercise on numerous occasions. Goodall et al. (2017) and Prasartwuth et al.

(2005) applied a fatiguing protocol involving eccentric elbow flexion for five sets of six repetitions at $30°\cdot s^{-1}$ MCV and five sets of ten repetitions at 30% of the predicted maximum eccentric force, respectively. Both studies found significant reductions in VA_{MNS} immediately after the fatiguing exercise. The studies also showed reductions in VA_{TMS} immediately after the exercise. However, the effect was only deemed statistically significant in the experiment of Goodall et al. (2017), whereas Prasartwuth et al. (2005) reported a non-significant trend for reduced VA_{TMS}. Prasartwuth et al. (2005) attributed their results to methodological decisions involving the normalization of the superimposed twitch to an estimated resting twitch. In addition to eccentric fatiguing protocols, VA_{MNS} was also significantly reduced after 4 min of sustained isometric MVCs of the dorsiflexor muscles (Kent-Braun, 1999). Furthermore, Thomas et al. (2018) found significant decreases in VA_{MNS} and VA_{TMS} immediately after ten sets of five repetitions in the back squat executed at 80% 1-RM.

Overall, it is difficult to conclude to what extent central mechanisms cause intra-set fatigue and, consequently, momentary failure, given the lack of research investigating central fatigue after single sets of resisted exercises performed to momentary failure under typical loading conditions. However, there is evidence suggesting that psychological mechanisms may affect the point of set termination when subjects are instructed to perform a set to voluntary (i.e., self-determined) failure, including self-evaluation of performance capacity and willingness to produce a maximum effort (Armes et al., 2020; Emanuel et al., 2020; Halperin et al., 2021; Souron et al., 2020). These effects may be particularly present in sets performed to failure at lighter loads compared to heavier loads (Halperin et al., 2021), which have been reported to yield higher levels of perceived discomfort among individuals (Farrow et al., 2021; Fisher et al., 2018; Fisher & Steele, 2017; Santos et al., 2021). Therefore, it could be hypothesized that the component of intra-set fatigue attributed to central processes may be mediated by psychological mechanisms. Further research is required to evaluate the contribution of other mechanisms.

Summary

In conclusion, various biological and psychological mechanisms contribute to exercise-induced fatigue in resistance training and depend on the duration and intensity of muscular contractions. However, certain biological mechanisms may specifically affect intra- and inter-set fatigue. For example, while reduced ATP resynthesis and increased serum NH_3 may predominantly explain inter-set fatigue, increased P_i, H^+, and extracellular K^+ may provide a basis to explain intra-set fatigue during resistance training on a peripheral level. Unfortunately, the exact mechanisms and their respective relevance for the development of intra-set fatigue remain unclear *in vivo* since multiple studies failed to replicate the influence of these mechanisms under physiological temperatures. On a central level, research largely supports the idea of intra-set fatigue being affected by psychological processes, while the contribution of other mechanisms targeting central drive is yet to be determined.

1.1.3.4 Mechanical explanations of fatigue

While fatigue is most commonly associated with the central and peripheral mechanisms discussed in the previous sections, acute changes in mechanical attributes of the muscle-tendon unit may also contribute to a progressive loss in force production during sustained or repetitive contractions. As such, the current section will briefly discuss the acute changes in muscle architecture and tendinous tissue compliance that can modulate exercise-induced fatigue.

One major component of muscle architecture that has been shown to experience acute changes during exercise is the pennation angle (PA). In particular, a muscle's PA is associated with the force output during contraction, because it determines what proportion of muscle cell force (F_{mc}) can be transmitted to the muscle's line of action (Roberts et al., 2019). The force being transmitted to the muscle's effective direction (F_{eff}) can be estimated using trigonometric functions as follows:

$$F_{eff}\ [N] = F_{mc}\cos(PA) \tag{9}$$

Therefore, as PA increases to a theoretical limit of 90°, F_{eff} approximates a value of 0 following a curvilinear decay (Figure 3). An acute exercise-induced increase in PA would therefore reduce a muscle's effective force output, even if other central and peripheral fatiguing mechanisms remained unaltered and, thus, contribute to the gradual loss of force production associated with muscular fatigue.

Indeed, numerous studies reported acute systematic changes in muscle architecture following a fatiguing exercise bout. Csapo et al. (2011) identified a 10% increase in PA and a 2% reduction in fascicle length in the vastus lateralis immediately after a single set of unilateral leg press performed to failure at the individual load that maximizes power output. They further observed that these changes slowly returned to baseline levels over the course of 30 min. Vieira et al. (2018) also reported significant increases in muscle thickness and PA in the vastus lateralis after 50 concentric knee extensions on an isokinetic dynamometer. Interestingly, the authors found no equivalent alterations following a work-matched eccentric knee extension protocol, indicating that acute changes in muscle architecture may depend on the contraction mode, the total duration of the exercise, and the exercise intensity.

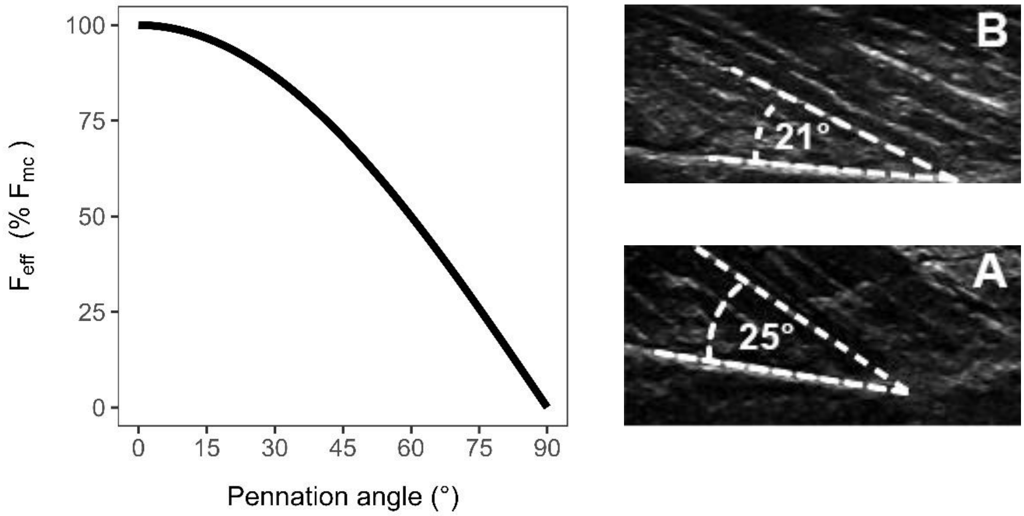

Figure 3. Association between effective muscular force and pennation angle. Left panel: effective muscular force (E_{eff}) expressed as a function of pennation angle (PA). E_{eff} yields the amount of muscle cell force (F_{mc}) transmitted to the muscle's effective direction. PA is expressed in a theoretical range of 0° to 90° to illustrate the geometric relationship. Right panel: example for acute alterations in vastus lateralis PA before (B) and after (A) exhaustive muscular work.

Increases in PA have also been reported after three sets of eight repetitions on the leg extension at 85% 1-RM (Martín-Hernández et al., 2013), as well as following an incremental ergometer test performed to exhaustion (Brancaccio et al., 2008). Moreover, Maganaris et al. (2002), reported that increases in PA and reductions in fascicle length were most pronounced during the first few repetitions of a set of ten short isometric plantarflexions performed at 80% MVC, suggesting that changes in muscle architecture may already occur in the early stages of a resistance training set.

As related to tendinous tissue compliance, Obst et al. (2013) stated, based on a systematic review, that the Achilles tendon may experience acute decreases in stiffness (tendon creep), hysteresis, and diameter following various loading tasks, including stretching, and resisted exercises for the calf muscles. According to these authors, changes were most pronounced after prolonged static stretching and isometric MVCs, leading to the conclusion that acute changes in tendinous tissue compliance may be mediated by tensile loading intensity and total duration of loading (Tardioli et al., 2012). Acute exercise-induced increases in Achilles tendon length and reductions in stiffness have further been reported as more pronounced in women than men (Joseph et al., 2014). However, whether decreases in tendon stiffness and hysteresis negatively affect force production is still subject to debate. On the one hand, it has been suggested that increased tendinous tissue compliance may benefit performance in certain repetitive movement tasks, such as sprinting, by contributing more elastic energy to dynamic contractions (Tardioli et al., 2012). On the other hand, some authors suggest that it may reduce peak isometric force and shift the muscle-tendon unit's length-tension relationship towards greater muscle lengths (Lemos et al., 2008; Philippou et al., 2009).

Indeed, tendon mechanics may indirectly affect fatigue-induced force loss, which is mediated by changes in muscle architecture (Csapo et al., 2011). This hypothesis is supported by research showing that increases in tendinous tissue compliance and increases in muscle PA occur simultaneously to some degree (Kubo et al., 2001; Lemos et al., 2008; Maganaris et al., 2002; Pearson & Onambele, 2005). In summary, acute mechanical changes in the muscle-tendon unit may contribute to an exercise-induced loss in force production due to transient increases in tendon compliance that facilitate an increase in muscle PA. However, based on the available evidence, it is impossible to tell to what extent these effects account for intra-set fatigue in the presence of other central and peripheral mechanisms.

1.2 Modeling physical performance

1.2.1 Statistical modeling in exercise science and practice

Due to the rapid advance in technological resources and the related rise of big data and machine learning in sports, statistical modeling of physical performance has recently received growing interest. Notably, modeling physical performance is not exclusively limited to experimental research settings but has been increasingly applied by practitioners to better guide training-related decisions. The implementation of statistical modeling has been suggested to focus on three main objectives: description, prediction, and causal inference (Hernán et al., 2019; Raita et al., 2021; Sanders, 2019).

Descriptive statistics are typically applied to summarize data samples, either by quantifying univariate features (e.g., measures of frequency, proportion, central tendency, and variability) or by quantifying multivariate relationships (e.g., linear regressions) (Hernán et al., 2019; Kaur et al., 2018). In training monitoring, descriptive statistics can be used to summarize an individual's internal and external training load over specific time frames (Clarke & Skiba, 2013; Impellizzeri et al., 2019; B. R. Scott et al., 2016). Diagnostic technology also commonly implements descriptive statistics during data processing to facilitate user interpretation. As an example, systems for monitoring movement velocity or power output in resistance training typically summarize data for each detected concentric repetition by displaying mean or peak values (Mitter, Hölbling, et al., 2021; Weakley et al., 2021).

Predictive statistics, in turn, apply derived features of observed data and prior assumptions (e.g., assumptions about the underlying model) to unobserved data (Hernán et al., 2019; Raita et al., 2021). Typically, this involves estimating the parameters of a statistical model from the data we know and using it to calculate the output that maximizes the conditional probability for a given input based on interpolation or extrapolation (Rabinowicz & Rosset, 2020; Sanders, 2019). Notably, predictions may yield varying degrees of accuracy and precision, depending on numerous factors such as sample size, model validity (i.e., representativeness of the latent underlying association), the proximity of the predictor to the model training data and the variance of model residuals (Figure 4).

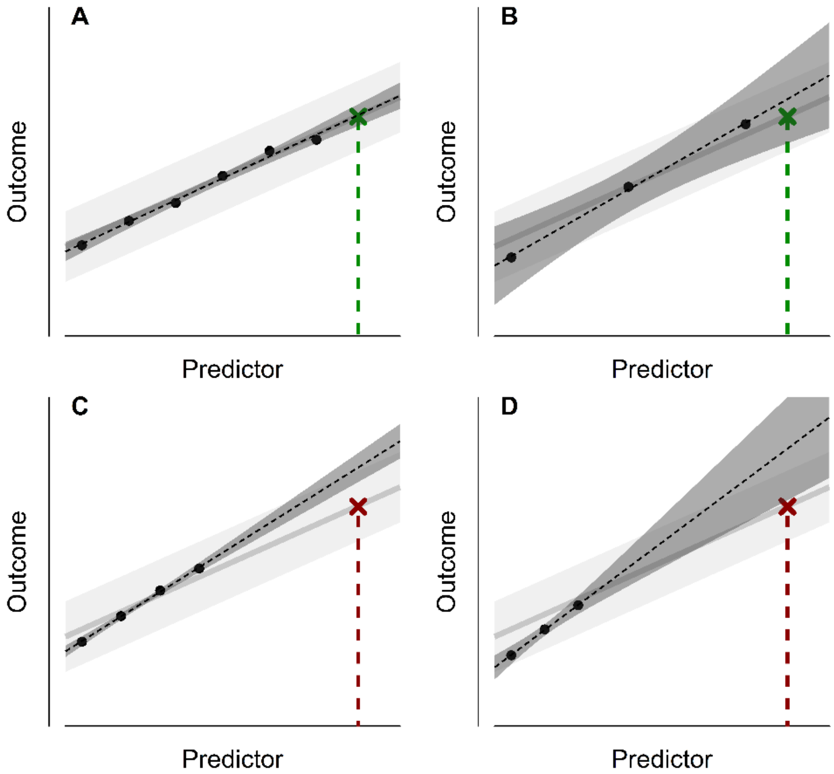

Figure 4. Different combinations of predictive accuracy and precision (illustration). Light grey lines and areas display population trends and their variation. Black dots display model training data sampled from the population trend. Dashed lines and dark grey areas represent models and 95% confidence intervals, respectively. Colored X's and colored dashed lines represent an ideal target for prediction at the center of the population trend (the point is not part of the training data). A, high accuracy and high precision; B, high accuracy and low precision; C, low accuracy and high precision; D, low accuracy and low precision.

In theory, there is extensive applicability for predictive statistics in sports, including the prognosis of training-induced adaptation based on fitness-fatigue models, and the prediction of physical performance given specific exercise conditions (Clarke & Skiba, 2013). For example, models of the relationship between load and maximum voluntary movement velocity in a given resistance training exercise have been applied to predict one's 1-RM load from sets performed at submaximal loads (Hughes et al., 2019). When estimated for single individuals, these so-called *load-velocity profiles* could also be applied to prescribe intended training loads in an autoregulatory fashion based on target movement velocities. This prescriptive approach has been suggested to overcome certain limitations of strategies that prescribe load as a percentage of a previously tested 1-RM load, by taking into account the athlete's contemporary readiness to perform (Larsen et al., 2021; Weakley et al., 2021).

The application of performance modeling is not restricted to the field of resistance training. In endurance sports, models of the relationship between time-to-exhaustion and running velocity (i.e., *critical speed* models) or power output in cycling (i.e., *critical power* models) have been advocated for the prediction of the best performance time an athlete can achieve for a given distance or amount of physical work (Vanhatalo et al., 2011). Estimated parameters of these models have also been reported to correlate well with metabolic and functional thresholds, including the maximum lactate steady state (MLSS) and the respiratory compensation point (RCP). Therefore, such predictive models may be used to approximate respective thresholds without the need for expensive technology to analyze capillary blood and respiratory gas (Galán-Rioja et al., 2020).

Finally, *causal inference* is typically assessed through counterfactual prediction. It is used to deduce causal relationships from statistical models considering the temporality of data and expert knowledge about the domain of the investigated causal structure (Hernán et al., 2019; Raita et al., 2021). It provides information on the hypothetical data-generating process and may facilitate or support the prescription of specific actions (Sanders, 2019). In the field of physical training, causal inference is an important objective of research in its quest to explain certain phenomena and, ultimately, provide practitioners with generalized insights to make evidence-based decisions, especially in the absence of more convenient indicators (e.g., the individual responsiveness to certain stimuli).

1.2.2 Modeling strength endurance

As described in chapter 1.1.2, strength endurance in dynamic isoinertial exercises is typically characterized by the magnitude of the applied load and the number of repetitions that can be achieved before reaching momentary failure. Studying the bivariate relationship between load and RTF in dynamic resistance training exercises has a long history in sport science, with early work dating back to the 1960s. One of these early investigations was conducted by Martens (1965), who explored the relationships between maximum isometric strength and isometric muscular endurance, as well as maximum dynamic strength (i.e., 1-RM) and dynamic muscular endurance (i.e., repetitions with a standardized movement cadence) in the elbow flexion exercise at 37.5% of the individual maximum strength load. He did not identify any significant association between maximum strength and muscular endurance, irrespective of the type of muscle action performed. However, he reported considerable between-subject variance in the number of repetitions performed during the first experimental period (Trial No. 1; mean ± SD [min-max]: 41.2 ± 6.5 [28-52] repetitions). Furthermore, the within-subject variability across test-retest trials reported by the author corresponds to a standard error of measurement (SEM) of 3.5 repetitions (90% Highest Density Interval: [2.8, 4.8])[1]. Even though Martens (1965) did not acknowledge this information, the previously presented data yields evidence that relative strength endurance is characterized by larger between-subject variability than within-subject variability.

Over the past decades, the primary motivation behind strength-endurance models has been the formulation of equations to predict the 1-RM load from a set performed to momentary failure at a submaximal load. Some published predictive equations feature multiple linear regression models and, therefore, apply the 1-RM directly as a dependent variable (Cummings & Finn, 1998; Dohoney et al., 2002; Horvat et al., 2003; Julio et al., 2012; Kravitz et al., 2003; Kuramoto & Payne, 1995; Macht et al., 2016; Materko & Santos, 2009; Mayhew et al., 2002; Tan et al., 2015; Tucker et al., 2006; Whisenant et al., 2003). Other equations aimed to model the bivariate relationship between relative load and RTF to calculate the 1-RM from a predicted relative load ($load_{rel}$, expressed as % 1-RM) by factoring in the applied absolute load ($load_{abs}$, expressed in kg).

$$1 - RM\ [kg] = \frac{100}{load_{rel}}\ load_{abs} \tag{10}$$

Table 2 provides an overview of bivariate strength-endurance models available in the literature.

[1] The SEM and HDI were calculated independently by the author of the present thesis, using the raw data provided by Martens (1965) and the statistical approach described in publication 2.

Table 2. A list of published bivariate models of the strength-endurance relationship.

Source	Model type	Model equation
Adams und Beam (2014)	Linear	$load = 1 - 0.025\ RTF$
Berger (1961, as cited in Mayhew et al., 2004)	Exponential (2P)	$load^1 = 1.0261\ e^{-0.0262\ RTF}$
Berger (1970, as cited in Mayhew et al., 2008)	Linear	$load^1 = 1.0261 - 0.0262\ RTF$
Brown (1992, as cited in Mayhew et al., 2008)	Reciprocal	$load = 1/(0.9849 + 0.0338\ RTF)$
Brzycki (1993)	Linear	$load = 1.0278 - 0.0278\ RTF$
Desgorces et al. (2010)	Exponential (3P)	$load^2 = 0.679776 + 0.361115\ e^{-0.1240\ RTF}$ $load^3 = 0.207706 + 0.793412\ e^{-0.0302\ RTF}$
Lander (1985, as cited in Mayhew et al., 2008)	Linear	$load = 1.013 - 0.0267123\ RTF$
Lombardi (1989, as cited in Mayhew et al., 2008)	Power	$load = RTF^{-0.1}$
Mayhew et al. (1992)	Exponential (3P)	$load = 0.522 + 0.419\ e^{-0.055\ RTF}$
Mayhew, Kerksick, Lentz, Ware & Mayhew (2004)	Power	$load = 1.0124\ RTF^{-0.1036}$
Mayhew et al. (2008)	Exponential (2P)	$load = 0.90575\ e^{-0.0152\ RTF}$
O'Connor et al. (1989, as cited in Mayhew et al., 2008)	Reciprocal	$load = 1/(1 + 0.025\ RTF)$
Reynolds et al. (2006)	Exponential (3P)	$load^4 = 0.2641 + 0.7817\ e^{-0.0569\ RTF}$ $load^5 = 0.4847 + 0.5551\ e^{-0.0723\ RTF}$
Sakamoto und Sinclair (2006)	Exponential (3P)	$load^6 = 0.084204 + 0.842909\ e^{-0.0332\ RTF}$ $load^7 = 0.185896 + 0.771715\ e^{-0.0427\ RTF}$ $load^8 = 0.154593 + 0.778118\ e^{-0.0438\ RTF}$ $load^9 = 0.133629 + 0.814083\ e^{-0.0639\ RTF}$
Wathen (1994, as cited in Mayhew et al., 2008)	Exponential (3P)	$load = 0.488 + 0.538\ e^{-0.075\ RTF}$
Welday (1988, as cited in Mayhew et al., 2008) [10]	Reciprocal	$load = 1/(1 + 0.0333\ RTF)$

Model equations were transformed to express load (dependent variable) as a factor of the one-repetition maximum (1-RM) in the range [0, 1]. Factors can be transformed to relative loads (% 1-RM) through multiplication by 100.
1, adapted after communicated with the author; 2, using loads between 75% and 100% 1-RM; 3, using loads between 20% and 100% 1-RM; 4, leg press exercise; 5, chest press exercise; 6, ballistic movement; 7, fast tempo; 8, medium tempo; 9, slow tempo; 10, occasionally also labeled Epley formula; (2P), 2 parameters; (3P), 3 parameters; RTF, repetitions performed to failure.

Importantly, not all model equations originate from empirical research. As outlined by Richens and Cleather (2014) and Wood et al. (2002), numerous predictive equations stem from loading charts or were published in textbooks on resistance training without ever providing explicit details on their computation (Adams & Beam, 2014; Brown, 1992; Epley, 1985; Lander, 1985; O'Connor et al., 1989; Wathen, 1994). Other equations reportedly resulted from intuitive curve fitting on unpublished data (Brzycki, 1993; Lombardi, 1989).

1.2.2.1 Proposed model functions

Thus far, six different model functions (i.e., model types) have been proposed in the literature to quantify the strength-endurance relationship. First, a *linear regression model* has been applied by several authors (Adams & Beam, 2014; Berger, 1970; Brzycki, 1993; Lander, 1985):

$$load = a + b\ RTF \tag{11}$$

Brzycki (1993), while acknowledging that the strength-endurance relationship may, in fact, not be linear across its entire spectrum, suggested that a simple linear model may be a close enough approximation at loads allowing for ten repetitions or less. However, many authors proposed that the relationship between relative load and RTF follows a curvilinear trend (e.g., Brechue & Mayhew, 2009; Desgorces et al., 2010; Mayhew et al., 2008; Reynolds et al., 2006). To account for a curvilinear pattern in the strength-endurance relationship, some authors seemingly adapted the linear model by applying a reciprocal transformation to load as dependent variable, yielding 1/load (Brown, 1992; O'Connor et al., 1989; Welday, 1988) [2]. Thus, rearranging the previous model equation, the curvilinear trend could be expressed as follows:

$$load = \frac{1}{a + b\ RTF} \tag{12}$$

[2] Equations provided by these authors were originally arranged to predict the 1-RM load from a submaximal load and the RTF achieved at it, the load being expressed in a unit of mass ($load_{abs}$): 1-RM = (a + b RTF) $load_{abs}$. It is important to note that, due to the absence of a rationale behind the models, the intended model function can only be assumed. For example, the addressed equations could theoretically be interpreted as multiple linear regressions featuring the 1-RM load as a dependent variable, a coefficient for $load_{abs}$ (a) and a coefficient for the product term RTF x $load_{abs}$ (b). However, it is highly uncommon to express multiple linear regression models without a constant additive term (intercept), making it an unlikely candidate as originally intended model function. When dividing both sides of the original equation by $load_{abs}$, the resulting equation would yield a simple linear regression, with the dependent variable being the inverse of relative load, and expressed as a factor. Therefore, the inverse transformation of the dependent variable is assumed as the intended modeling approach by the addressed authors.

Due to the characteristic transformation, eq. 12 will be referred to as the *reciprocal regression model* throughout this manuscript. Interestingly, two of the three sources mentioned above applied an "a" parameter of 1 (O'Connor et al., 1989; Welday, 1988). However, this represents a questionable simplification or rounding of the parameter, as an intercept of 1 suggests the 1-RM to occur at 0 repetitions, making model equations proposed by O'Connor et al. (1989) and Welday (1988) logically conflicting. Assuming that the parameter "b" is a positive number, "a" would rather be expected to be smaller than 1, as shown in the equation proposed by Brown (1992).

Lombardi (1989), in turn, proposed a predictive equation for the 1-RM load based on a power function featuring a single exponential parameter. This model was also adopted by Mayhew et al. (2004), who further introduced a multiplicative parameter. Accordingly, the equation originally presented by Mayhew et al. (2004) can be rearranged to represent the strength-endurance relationship as follows:

$$load = a\ RTF^{b} \tag{13}$$

Importantly, outcomes predicted from power models are typically susceptible to predictor input, especially if the effect of the exponential parameter is not mitigated by other model terms (e.g., multiplicative or additive terms). This was also confirmed by Mayhew et al. (2004), who reported worse cross-validation performance of the power function compared to the linear and exponential functions. Therefore, the power function is only mentioned for historical reasons and will not be discussed further in the present thesis.

Another approach to account for a curvilinear relationship has been suggested in the form of a *3-parameters exponential regression model* (Desgorces et al., 2010; Mayhew et al., 1992; Reynolds et al., 2006; Sakamoto & Sinclair, 2006; Wathen, 1994). The model features a multiplicative ("a"), an exponential ("b"), and an additive parameter ("c"), with an asymptote of $f(x) = c$:

$$load = c + a\ e^{b\ RTF} \tag{14}$$

Berger (1961, as cited in Mayhew et al., 2004) and Mayhew et al. (2008) further proposed a simplified version of the exponential regression by omitting the additive parameter "c", yielding a *2-parameters exponential regression model:*

$$load = a\ e^{b\ RTF} \tag{15}$$

Eq. 15 could also be derived from a linear regression model (eq. 11) after applying a natural log transformation to load as dependent variable. For details, see section 8.1 (Appendix A).

Finally, the most recent addition to strength-endurance models has been proposed by R. H. Morton et al. (2014), who investigated the transferability of the critical power model to resistance training. Monod and Scherrer (1965) originally introduced the critical power model to quantify the maximum physical work produced during local muscular action as a function of a given time limit. In their article, Monod and Scherrer (1965) ascribed biological meaning to the parameters of their proposed model, stating that they reflect circulatory conditions within the muscle and the muscle's energy reserve. Since their pioneering work, the critical power model has drawn much attention in endurance sports and has been refined multiple times, for example, to yield physical power (P) as a dependent variable rather than work (Clarke & Skiba, 2013). One of the alterations of the early critical power model was proposed by Moritani et al. (1981), who suggested a linear regression model that accounted for the curvilinear relationship between P and t_{lim} by introducing a reciprocal transformation on t_{lim} as the independent variable:

$$P = CP + W' \frac{1}{t_{lim}} \tag{16}$$

In eq. 16, CP (critical power) represents the power-asymptote, and W' (occasionally labeled *anaerobic work capacity*, AWC) represents the model curvature. This model was later complemented by a third parameter to introduce a variable time-asymptote (k) and, therefore, allow for an axis-intercept (P_{max}) at t_{lim} = 0 (R. H. Morton, 1996):

$$P = \frac{W'}{t_{lim} - k} + CP$$
$$k = \frac{W'}{CP - P_{max}} \tag{17}$$

While the critical power model originally found application in various endurance-oriented physical activities such as cycling, running, swimming, and rowing (Clarke & Skiba, 2013), R. H. Morton et al. (2014) hypothesized that the model could eventually be applied to dynamic resistance training exercises, which display a similarly repetitive or cyclic movement pattern. The authors proposed that in resistance exercises, power output could be expressed as the product of mass (i.e., load), acceleration due to gravity (g), distance (i.e., range of motion, d), and movement cadence (i.e., repetitions per minute, c), using the following equation:

$$P = \frac{load\ g\ d\ c}{60} \tag{18}$$

Assuming that the range of motion and movement cadence are held constant, power output is directly proportional to the applied load. Furthermore, since the time to exhaustion is defined by RTF at a constant movement cadence, t_{lim} could be expressed as follows:

$$t_{lim} = RTF\frac{60}{c} \quad (19)$$

By maintaining the abovementioned assumptions, t_{lim} would be directly proportional to RTF [3]. Consequently, R. H. Morton et al. (2014) suggested that the variables P and t_{lim} outlined in the critical power model (eq. 17) could be replaced by load and RTF when applying the model for resistance exercises. The authors proposed alternative labels for the model parameters to account for these changes in model variables. Specifically, W' became *anaerobic lift capacity* (ALC), CP became *critical lift* (CL), and P_{max} became L_{max}:

$$\begin{aligned} load &= \frac{ALC}{RTF - k} + CL \\ k &= \frac{ALC}{CL - L_{max}} \end{aligned} \quad (20)$$

Over the past years, the model has been given different names based on the parameter labels chosen, such as the *critical resistance model* (Dinyer, Byrd, Succi, & Bergstrom, 2020; Dinyer, Byrd, Vesotsky, Succi, & Bergstrom, 2019; Dinyer, Byrd, Vesotsky, Succi, Clasey, & Bergstrom, 2019) or the *critical load model* (Arakelian et al., 2017; Arakelian et al., 2018; Arakelian et al., 2019; Dinyer, Byrd, Succi, Clasey, & Bergstrom, 2020; Dinyer, Byrd, Vesotsky, et al., 2020; Moss et al., 2021). A recent review by Bergstrom et al. (2021) proposed the unification of terminology, officially calling it the critical load model and proposing the following parameter labels: L' instead of ALC as the curvature constant, and CL as critical load, yielding the following final equation:

$$\begin{aligned} load &= \frac{L'}{RTF - k} + CL \\ k &= \frac{L'}{CL - L_{max}} \end{aligned} \quad (21)$$

1.2.2.2 Potential applications of strength-endurance models

Thus far, the application of strength-endurance models in research and practice has typically been focused on predicting the 1-RM load based on a set performed to failure at submaximal loads. However, strength-endurance models can also predict the load associated with any given repetition maximum (n-RM). When interpolating and extrapolating loads

[3] As a side note, it should be mentioned that while these explanations follow logical reasoning, they display an oversimplification of mechanic processes and lack ecological validity. First, the force applied in resistance training is not solely determined by the exercise load and acceleration due to gravity, but also a dynamic acceleration component that is required to overcome inertia. Second, standardizing the tempo or cadence of a movement may not be reasonable under all circumstances.

across a broader range of n-RM, these predictions can also be summarized in the form of repetition maximum tables or loading charts, providing practitioners the means for quick orientation across the strength-endurance spectrum when designing resistance training programs (Chapman et al., 1998; Epley, 1985; Haff & Triplett, 2016; Lander, 1985; Lorenz et al., 2010; Mayhew et al., 1993; Morales & Sobonya, 1996). Table 3 summarizes predicted relative loads for repetition maxima in the 1-RM to 20-RM range using the model equations shown in Table 2.

Assuming that a specific strength-endurance model yields a valid representation of someone's capabilities, predictions could further be used to prescribe submaximal levels of effort in a continuous normalized fashion. This may be of substantial interest to researchers investigating the role of effort in training-induced adaptations. So far, research has predominantly dichotomized the intensity of effort into either training to failure (i.e., applying maximal effort) or not to failure (i.e., applying submaximal effort), without any further consideration to how close to failure the submaximal effort was. This dichotomization of effort, unfortunately, rules out the possibility of drawing inferences on a dose-response relationship and leaves training to failure as the only objective approach to standardizing effort between and within individuals (Fisher et al., 2022; Steele, Fisher, et al., 2017). Therefore, identifying a reliable method of quantifying the intensity of effort as a continuous variable may offer novel opportunities to understand effort as a potential mediator of adaptation processes.

Apart from its considerable value for research, the quantification of effort may also interest practitioners. It has commonly been proposed that resistance exercise should be performed to failure, or close to it, to maximize muscle fiber recruitment and stimulate muscle hypertrophy and strength gains (Fisher et al., 2022; Iversen et al., 2021). This approach, however, may not be ideal under certain circumstances. For example, adaptations in explosive performance have been shown to benefit from a lower intensity of effort during a training regimen in resistance-trained individuals (Alcazar et al., 2021; Izquierdo-Gabarren et al., 2010; Pareja-Blanco et al., 2017; Pareja-Blanco, Alcazar, et al., 2020). These findings may, to some extent, be explained by the fact that lower levels of intra-set fatigue allow for better maintenance of explosive performance throughout the training session (Fonseca et al., 2020; Morán-Navarro et al., 2017; Pareja-Blanco et al., 2019; Pareja-Blanco, Rodríguez-Rosell, et al., 2020; Piqueras-Sanchiz et al., 2021; Sánchez-Medina & González-Badillo, 2011).

Table 3. Strength-endurance models expressed as repetition maximum tables

	Repetition maximum (n-RM)									
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Adams and Beam (2014)	98%	95%	93%	90%	88%	85%	83%	80%	78%	75%
Berger (1961, as cited in Mayhew et al., 2004)	100%	97%	95%	92%	90%	88%	85%	83%	81%	79%
Berger (1970, as cited in Mayhew et al., 2008)	100%	97%	95%	92%	90%	87%	84%	82%	79%	76%
Brown (1992, as cited in Mayhew et al., 2008)	98%	95%	92%	89%	87%	84%	82%	80%	78%	76%
Brzycki (1993)	100%	97%	94%	92%	89%	86%	83%	81%	78%	75%
Desgorces et al. (2010)	100%	96%	93%	90%	87%	85%	83%	81%	80%	78%
Lander (1985, as cited in Mayhew et al., 2008)	99%	96%	93%	91%	88%	85%	83%	80%	77%	75%
Lombardi (1989, as cited in Mayhew et al., 2008)	100%	93%	90%	87%	85%	84%	82%	81%	80%	79%
Mayhew et al. (1992)	92%	90%	88%	86%	84%	82%	81%	79%	78%	76%
Mayhew et al. (2004)	101%	94%	90%	88%	86%	84%	83%	82%	81%	80%
Mayhew et al. (2008)	89%	88%	87%	85%	84%	83%	81%	80%	79%	78%
O'Connor et al. (1989, as cited in Mayhew et al., 2008)	98%	95%	93%	91%	89%	87%	85%	83%	82%	80%
Reynolds et al. (2006) [1]	100%	96%	92%	89%	85%	82%	79%	76%	73%	71%
Reynolds et al. (2006) [2]	100%	97%	93%	90%	87%	84%	82%	80%	77%	75%
Sakamoto and Sinclair (2006)	93%	89%	86%	84%	81%	78%	76%	73%	71%	69%
Wathen (1994, as cited in Mayhew et al., 2008)	99%	95%	92%	89%	86%	83%	81%	78%	76%	74%
Welday (1988, as cited in Mayhew et al., 2008) [3]	97%	94%	91%	88%	86%	83%	81%	79%	77%	75%
Mean	98%	94%	92%	89%	86%	84%	82%	80%	78%	76%
SD	3%	3%	3%	2%	2%	2%	2%	2%	3%	3%

Predictions are expressed as % of one-repetition maximum (1-RM).
1, model for leg press exercise; 2, model for chest press exercise; 3, occasionally also labeled “Epley” formula; SD, standard deviation.

Table 3. (continued) Strength-endurance models expressed as repetition maximum tables

Model	Repetition maximum (n-RM)									
	11	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Adams and Beam (2014)	73%	70%	68%	65%	63%	60%	58%	55%	53%	50%
Berger (1961, as cited in Mayhew et al., 2004)	77%	75%	73%	71%	69%	67%	66%	64%	62%	61%
Berger (1970, as cited in Mayhew et al., 2008)	74%	71%	69%	66%	63%	61%	58%	55%	53%	50%
Brown (1992, as cited in Mayhew et al., 2008)	74%	72%	70%	69%	67%	66%	64%	63%	61%	60%
Brzycki (1993)	72%	69%	67%	64%	61%	58%	56%	53%	50%	47%
Desgorces et al. (2010)	77%	76%	75%	74%	74%	73%	72%	72%	71%	71%
Lander (1985, as cited in Mayhew et al., 2008)	72%	69%	67%	64%	61%	59%	56%	53%	51%	48%
Lombardi (1989, as cited in Mayhew et al., 2008)	79%	78%	77%	77%	76%	76%	75%	75%	74%	74%
Mayhew et al. (1992)	75%	74%	73%	72%	71%	70%	69%	68%	67%	66%
Mayhew et al. (2004)	79%	78%	78%	77%	76%	76%	75%	75%	75%	74%
Mayhew et al. (2008)	77%	75%	74%	73%	72%	71%	70%	69%	68%	67%
O'Connor et al. (1989, as cited in Mayhew et al., 2008)	78%	77%	75%	74%	73%	71%	70%	69%	68%	67%
Reynolds et al. (2006) [1]	68%	66%	64%	62%	60%	58%	56%	54%	53%	51%
Reynolds et al. (2006) [2]	74%	72%	70%	69%	67%	66%	65%	64%	63%	62%
Sakamoto and Sinclair (2006)	67%	65%	63%	61%	59%	58%	56%	54%	53%	51%
Wathen (1994, as cited in Mayhew et al., 2008)	72%	71%	69%	68%	66%	65%	64%	63%	62%	61%
Welday (1988, as cited in Mayhew et al., 2008) [3]	73%	71%	70%	68%	67%	65%	64%	63%	61%	60%
Mean	74%	72%	71%	69%	67%	66%	64%	63%	61%	60%
SD	3%	4%	4%	5%	6%	6%	7%	8%	8%	9%

Predictions are expressed as % of one-repetition maximum (1-RM).
1, model for leg press exercise; 2, model for chest press exercise; 3, occasionally also labeled “Epley” formula; SD, standard deviation.

Furthermore, the accumulation of exercise-induced fatigue has also been associated with negative changes in affective valence and greater feelings of discomfort, especially when sets to failure are performed at lighter loads (Cavarretta et al., 2022; Kaus, 2014; Orssatto et al., 2020; Ribeiro et al., 2019). Indeed, experiencing high levels of effort too frequently may result in a negative affective valuation of training, providing a reason for practitioners to regulate and vary the intensity of effort in a controlled fashion, which may help maintaining trainees' adherence to the training program (Cavarretta et al., 2019b, 2019a).

Thus far, research has suggested two approaches to normalize intensity of effort on a continuous scale, which will be covered in detail in the following sections.

Relative intensity of set-repetition best

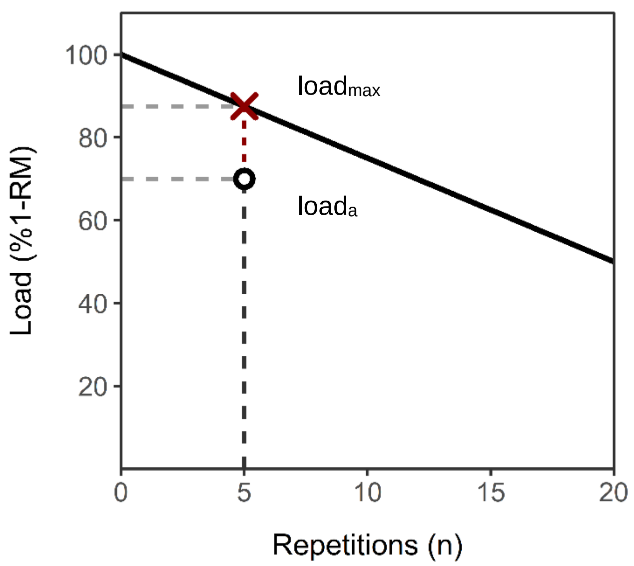

Figure 5. Relative intensity of set-repetition best (illustration). The solid black line displays the assumed strength-endurance model (Adams and Beam, 2014). The black circle portrays an exemplary set at submaximal effort (5 x 70% 1-RM). The red X displays the extrapolated maximum load that could theoretically be applied for a given volume of 5 repetitions, according to the strength-endurance model. 1-RM, one-repetition maximum; load$_a$, applied load; load$_{max}$, extrapolated maximum load.

Submaximal levels of effort can be quantified by expressing the applied load ($load_a$) as a proportion of the predicted maximum load ($load_{max}$) that could have been used for the same number of completed repetitions n_a (B. R. Scott et al., 2016). This concept is illustrated in Figure 5 and can be expressed mathematically as follows:

$$Applied\ set\ structure: \quad n_a \times load_a$$

$$RI_{SR} = \frac{load_a}{load_{max}} \tag{22}$$

$$load_{max} = f(n_a)$$

Under the assumption that a person's strength-endurance relationship follows the model described by Adams and Beam (2014), an exercise set performed with five repetitions at 70% 1-RM would correspond to an effort of about 80% 5-RM (i.e., 70/88; 70%-1RM being the applied load and 88% 1-RM being the predicted maximum load that could be chosen for a target of 5 repetitions, as shown in Table 3).

To the author's knowledge, this concept was originally introduced by M. H. Stone and O'Bryant (1987). Since then, it has been communicated under names such as the *relative intensity using specific set and repetition configurations* (Carroll, Bazyler, et al., 2019; Carroll, Bernards, et al., 2019; DeWeese et al., 2015) or as the *relative intensity of set-repetition best* (Suchomel et al., 2021). Throughout this thesis, the concept will be addressed using the acronym RI_{SR}.

Relative effort

The intensity of effort can also be quantified as the proximity to momentary failure at the set endpoint based on the number of actually performed repetitions and the maximum achievable number of repetitions (n_{max} or *RTF*) for a given load (Figure 6). Research has recently proposed the term *relative effort* (RE) for this kind of normalization (Steele, Endres, et al., 2017; Steele, Fisher, et al., 2017):

$$Applied\ set\ structure: \quad n_a \times load_a$$

$$RE = \frac{n_a}{n_{max}} \tag{23}$$

$$n_{max} = f(load_a)$$

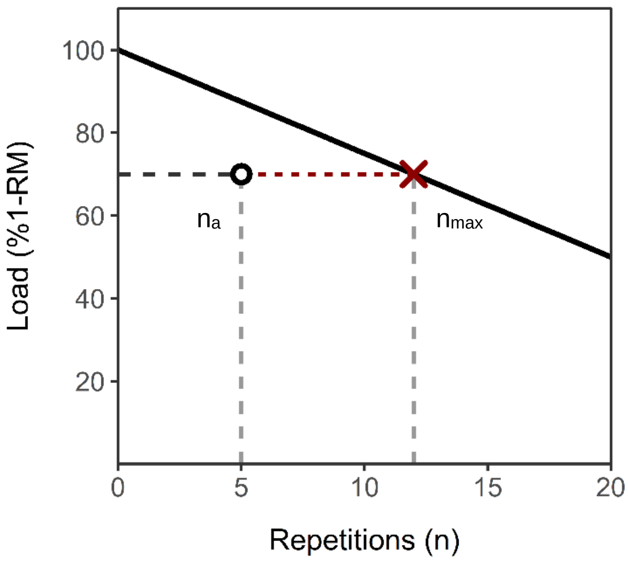

Figure 6. Relative effort (illustration).
The solid black line displays the assumed strength-endurance model (Adams and Beam, 2014). The black circle portrays an exemplary set at submaximal effort (5 x 70% 1-RM). The red X displays the extrapolated maximum number of repetitions that could theoretically be performed at a given load of 70% 1-RM, according to the strength-endurance model. 1-RM, one-repetition maximum; n_a, applied repetitions; n_{max}, extrapolated maximum number of repetitions.

Applying the model proposed by Adam and Beam (2014) and the same set structure as in the previous example (5 x 70% 1-RM), a relative effort of about 42% n_{max} can be calculated (i.e., 5/12; 5 being the number of repetitions performed and 12 being the maximum number of repetitions that could have been performed at 70% 1-RM before reaching momentary failure according to Table 3).

RE can also be estimated retrospectively without using strength-endurance models, but by predicting n_{max} in an alternative way after the end of each exercise set. For this purpose, athletes can, for example, resort to subjectively estimating the repetitions in reserve (RIR) based on the self-evaluation of their performance or the perceived proximity to failure at the set endpoint. This estimate could then be added to the number of repetitions that were performed, as follows:

$$n_{max} = n_a + RIR \tag{24}$$

However, this approach assumes a high agreement between perceived proximity to failure and actual proximity to failure, which is conceptually questionable (Steele, 2021). Indeed, this may not always been the case, especially when a set endpoint occurs far from failure and at lighter loads (Halperin et al., 2021).

Practitioners can also utilize the velocity of the fastest repetition in a set as a predictor of n_{max} (Miras-Moreno et al., 2022) or predict RE from the reduction in maximum voluntary movement velocity between the first (or fastest) and last repetition of a specific exercise set (Hernández-Belmonte et al., 2021; Rodríguez-Rosell et al., 2020). However, these velocity-based approaches typically require reliable technology to assess movement velocity and assume that athletes perform each repetition with maximum intent (i.e., maximum voluntary velocity). Individuals who are not familiar with the execution of a given exercise at maximum intent may therefore experience higher variability of recorded performance (Grgic, Scapec, et al., 2020), especially when the equipment or technology used is subject to a more pronounced random measurement error (Courel-Ibáñez et al., 2019; Martínez-Cava et al., 2020). Naturally, this may affect predictions from statistical models using velocity as a predictor.

Proposing a new paradigm: vectorized relative effort

Even though RI_{SR} and RE represent different perspectives of a set's structure (load and volume, respectively), they both provide a reasonable approach to quantifying the intensity of effort for a given set. However, when applied to the same set structure, these two approaches usually lead to different relative magnitudes. As shown in the examples presented in the two previous sections, a set of five repetitions at 70% 1-RM yielded a RI_{SR} of ~80% and a RE of ~42%. Therefore, the two concepts cannot be used interchangeably, which challenges practitioners' ability to decide between them if they intend to normalize the intensity of effort. One possibility to eliminate the need to decide between the two approaches is developing a new concept that unifies both perspectives. This goal can be achieved by applying a geometric perspective (Figure 7) and expressing the load and number of repetitions applied as a position vector ($\overrightarrow{OA}$):

$$\overrightarrow{OA} = \begin{pmatrix} load_a \\ n_a \end{pmatrix} \tag{25}$$

The length of this vector can then be quantified as:

$$|\overrightarrow{OA}| = \sqrt{{load_a}^2 + {n_a}^2} \tag{26}$$

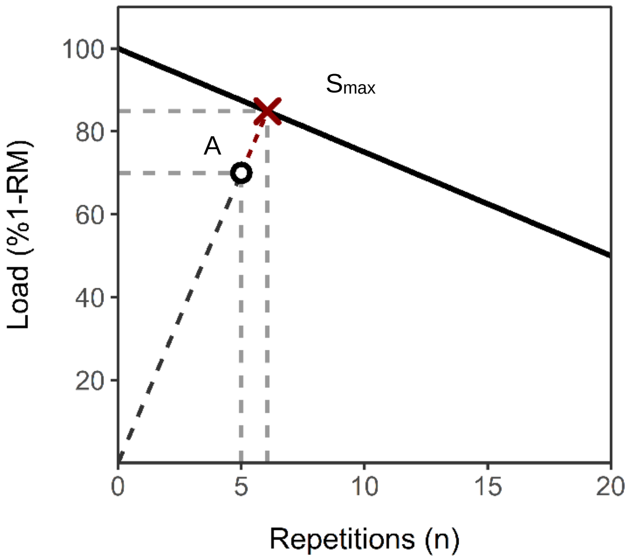

Figure 7. Vectorized relative effort (illustration).
The solid black line displays the assumed strength-endurance model (Adams and Beam, 2014). The black circle portrays an exemplary set at submaximal effort (5 x 70% 1-RM). The red X displays the extrapolated strength-endurance maximum that could theoretically be performed, according to the strength-endurance model, if the load-to-repetitions ratio is maintained. 1-RM, one-repetition maximum; A, applied set (n_a x $load_a$) expressed as geometric coordinates; S_{max}, extrapolated strength-endurance maximum with the same load-to-repetitions ratio.

When expressing $\overrightarrow{OA}$ as a linear function, it yields:

$$load = \frac{load_a}{n_a}\, n \tag{27}$$

The intersection between $\overrightarrow{OA}$ and the assumed strength-endurance model can now be calculated, which yields a point on the strength-endurance function with the same position vector orientation as the applied set (S_{max}). Thus, the coordinates of both position vectors are proportional by a factor φ:

$$\overrightarrow{OA} = \varphi\, \overrightarrow{OS}_{max} \tag{28}$$

Assuming once again that the model proposed by Adams and Beam (2014) provides a good representation of the individual strength-endurance relationship (i.e., $load = 1 - 0.025\,n$), the intersection can be expressed as follows:

$$\overrightarrow{OS}_{max} = \begin{pmatrix} load_{lim} \\ n_{lim} \end{pmatrix} = \begin{pmatrix} \dfrac{load_a}{load_a + 0.025\,n_a} \\ \dfrac{n_a}{load_a + 0.025\,n_a} \end{pmatrix} \tag{29}$$

A full derivation of eq. 29 is available in section 8.2 (Appendix B). As for eq. 26, the length of $\overrightarrow{OS}_{max}$ can then be quantified as:

$$\left|\overrightarrow{OS}_{max}\right| = \sqrt{{load_{lim}}^2 + {n_{lim}}^2} = \sqrt{\frac{{load_a}^2 + {n_a}^2}{(load_a + 0.025\,n_a)^2}} \tag{30}$$

Relative effort can then be expressed as the proportion between $\overrightarrow{OA}$ (eq. 26) and $\overrightarrow{OS}_{max}$ (eq. 30) vector lengths, which, once resolved, would yield the following:

$$RE_v = \varphi = \frac{\left|\overrightarrow{OA}\right|}{\left|\overrightarrow{OS}_{max}\right|} = \frac{load_a}{load_{lim}} = \frac{n_a}{n_{lim}} = load_a + 0.025\,n_a \tag{31}$$

For consistency, this novel concept will be addressed in the present thesis as the *vectorized relative effort* (RE_v). To provide an example, the previously mentioned set structure of 5 x 70% 1-RM would yield a RE_v of 82.5%. This value could be interpreted as an index of proximity to momentary failure from the perspective of a geometric origin rather than a given load (i.e., as in RE) or a given number of repetitions (i.e., as in RI_{SR}). Therefore, RE_v quantifies the proximity to failure based on a predicted performance limit that shares the same load-to-repetitions ratio as the set performed ($load_{lim}$ / n_{lim} = $load_a$ / n_a). However, it should be noted that, like the other approaches discussed before, the computation of RE_v for a set performed at submaximal effort requires users to assume a specific strength-endurance relationship.

1.2.2.3 Flaws in published strength-endurance models

While empirical research and textbooks have proposed many equations of fitted strength-endurance models over the past decades, different model functions have rarely been compared to provide a rigorous conclusion on which one yields the better approximation to the strength-endurance relationship. Both Reynolds et al. (2006) and Desgorces et al. (2010) fitted linear (eq. 11), and exponential models (eq. 14) to strength-endurance data and compared the variance explained (R^2) and standard error of estimate (SEE) between the two functions. Based on this comparison, both authors concluded that the exponential model was the better choice. Still, it is questionable whether R^2 and SEE alone constitute a reasonable basis for this conclusion since the two statistics only provide information about the model fit and, thus, only quantify the descriptive properties of a model.

As outlined in chapter 1.2.2.2, the main application of strength-endurance models revolves not around description but prediction. In contrast to the descriptive validity of a model, predictive accuracy is not necessarily represented by measures of in-sample model fit such as R^2 and SEE (Poldrack et al., 2020). The dichotomy of in-sample model fit and out-of-sample predictive accuracy is ultimately related to the issue of overfitting statistical models. While the model fit systematically increases with model complexity (e.g., by adding new parameters), the predictive accuracy of a model is determined by the magnitude of the total model error (i.e., the sum of error due to bias, variance and noise) (Gigerenzer & Brighton, 2009). However, total model error shares a different relationship with model complexity, which is well documented as the *bias/variance tradeoff* (Briscoe & Feldman, 2011; Poldrack et al., 2020; Waldmann, 2019). In principle, it states that the error due to inappropriate model assumptions (i.e., bias) and error due to sample-specific parameter estimates (i.e., variance) coexist and are to some degree inversely related. Therefore, bad predictive performance can result from too simplistic (i.e., underfitting) and too complex (i.e., overfitting) models, yielding the optimal level of model complexity somewhere in-between. Figure 8 illustrates the dichotomy of model fit and predictive accuracy with simulated data.

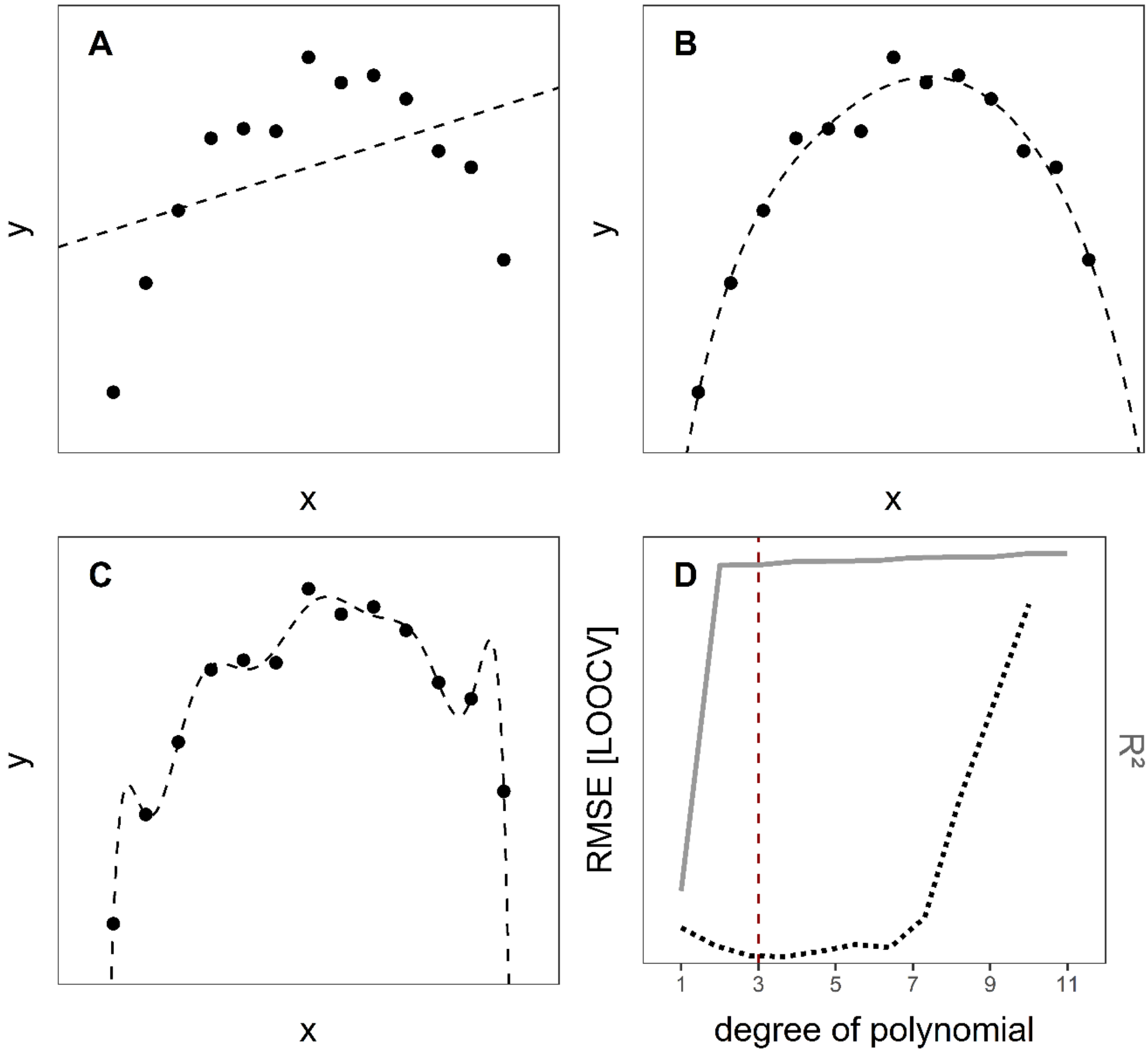

Figure 8. The dichotomy of model fit and predictive accuracy (illustration).

Panels A to C portray three model functions (dashed lines) at different levels of model complexity, as defined by the degree of polynomial fit: A, linear fit (1^{st}-degree polynomial); B, 6^{th}-degree polynomial fit; C, 11^{th}-degree polynomial fit. Panel D portrays the dichotomy of model fit and predictive accuracy: model fit (R^2, solid grey line) increases continuously as model complexity increases. Predictive accuracy is expressed as root mean squared error calculated from leave-one-out cross-validation (RMSE [LOOCV], dotted black line), which drastically increases from a certain level of complexity. The dashed red line marks the level of complexity with the highest predictive accuracy (i.e., lowest RMSE).

While predictive accuracy should be typically evaluated across the full spectrum of data using cross-validation, the best indicators to evaluate the predictive accuracy of published strength-endurance models are studies validating 1-RM predictive equations against a direct 1-RM assessment. Surprisingly, these studies reported heterogeneous findings between and within the investigated predictive equations. Welday‘s equation (1988, as cited by Mayhew et al., 2008), occasionally named after one of its most popular proponents, Boyd Epley, was found to either underpredict (LeSuer et al., 1997; Schwingel et al., 2009; Wood et al., 2002) or overpredict the 1-RM load (DiStasio, 2014; Mayhew et al., 2004; Nickerson et al., 2020; Ware et al., 1995). Similarly, Brzycki’s equation (1993) was also found to underpredict (DiStasio, 2014; LeSuer et al., 1997; Mayhew et al., 2008; McNair et al., 2011; Schwingel et al., 2009; Wood et al., 2002) and overpredict the 1-RM load (Mayhew et al., 2008; Ware et al., 1995). Moreover, numerous studies reported considerably large between-subject variance in predictive accuracy for all the equations investigated (Costa & Ribeiro Neto, 2018; Hetzler et al., 2010; Mayhew et al., 2008; McNair et al., 2011; Nickerson et al., 2020; Ribeiro Neto et al., 2017; Ware et al., 1995; Wood et al., 2002), despite some authors misinterpreting a non-significant difference between predicted and actual 1-RM as evidence for high accuracy (Ribeiro Neto et al., 2017; Schwingel et al., 2009). Researchers have also reported a trend towards higher predictive accuracy when the RTF test used as predictor was performed at a load allowing only for a small number of repetitions to be completed (Desgorces et al., 2010; Mayhew et al., 2008; Reynolds et al., 2006; Wood et al., 2002).

The most obvious explanation for the heterogeneous findings described above would be that the sample characteristics and experimental methodology varied substantially across the validation studies and, thus, may not have been representative of the original investigations that proposed the analyzed equations. In turn, the high between-subject variance in predictive accuracy could be explained by confounders that were not accounted for in the bivariate strength-endurance models. One such confounder that is commonly disregarded in validation studies is the type of exercise applied. Several studies reported significant differences between exercises in RTF performed at the same standardized relative load, the effect being most pronounced at lower relative loads (Arazi & Asadi, 2011; Hoeger et al., 1990; Shimano et al., 2006). Shimano et al. (2006) suggested that the number of RTF may depend on the muscle mass involved in a given exercise after reporting significantly higher RTF in the back squat than in the arm curl and, in certain conditions, the bench press. Comparable results were also reported by Arazi and Asadi (2011). Furthermore, Reynolds et al. (2006) found that the relationship between relative load and RTF differed between the chest press and leg press exercise, and trends continuously diverged as relative load decreased.

Another exercise-related confounder that has been reported to affect the number of repetitions attained at standardized relative loads is movement cadence (i.e., tempo). In particular, the use of a higher movement tempo has repeatedly been shown to allow for a greater number of repetitions to be performed before reaching momentary failure (Buitrago et al., 2012; LaChance & Hortobagyi, 1994; R. W. Morton et al., 2019; Sakamoto & Sinclair, 2006). However, this phenomenon cannot be entirely explained by the total time under tension: Buitrago et al. (2012) found significant differences in total exercise duration when comparing different movement cadences to a condition where subjects performed the concentric phase at maximum voluntary velocity. Similar differences in time under tension were also reported by R. W. Morton et al. (2019).

Aside from exercise-related confounders, there is also evidence of biological factors influencing the strength-endurance relationship. It has been suggested that, on average, women may be less fatigable than men, although this effect has been considered task-specific (Hunter, 2009). Hoeger et al. (1990) reported descriptive statistics on the number of RTF that indicate significant differences between men and women for certain exercises, at a .05 alpha level [4]. These differences were most prominent in untrained individuals and at lighter loads. However, in certain conditions, men performed significantly more repetitions than women at standardized relative loads (e.g., in the knee extension at 40% 1-RM in trained individuals or the arm curl at 80% 1-RM in untrained individuals). Dinyer, Byrd, Vesotsky, Succi, Clasey, and Bergstrom (2019) assessed men and women for their individual critical load in the deadlift. While they reported the critical load to be at a significantly higher percentage of the 1-RM in women compared to men (mean ± SD: 41 ± 2 % 1-RM and 37 ± 6 % 1-RM, respectively), women also achieved significantly more RTF at the critical load as compared to men (58 ± 12 vs. 45 ± 14 repetitions, respectively).

The difference in relative strength endurance between men and women appears to be task-specific rather than a uniform effect across different exercises and loads. As such, it could be reasoned that there might be a different causal factor influencing the number of RTF completed at a given load, which is merely mediated by biological sex. It seems reasonable to assume that intra-set fatiguability and, thus, strength endurance are determined by the capacity of psycho-physiological systems to counteract fatigue-related processes. Douris et al. (2006) investigated the relationship between the distribution of muscle fiber types and

[4] Independent t-tests were completed by the author of the present thesis based on descriptive statistics presented by Hoeger et al., (1990).

the number of RTF performed at 70% 1-RM in the leg extension exercise. The authors reported a significant negative effect of the proportion of type II muscle fibers on the number of RTF completed (r = -0.48). Since type II muscle fibers have been reported as more susceptible to fatigue than type I fibers, their findings support the conclusion that a greater proportion of easily fatigable muscle fibers in the working muscle would predispose to a lower number of repetitions to be performed at moderate relative loads. Notably, the authors did not acquire information on the fiber type distribution based on muscle biopsies but predicted the proportion of type II fibers based on an isokinetic assessment protocol. In contrast, Terzis et al. (2008) determined fiber type distribution through actual muscle biopsies of the vastus lateralis and observed only minor non-significant associations between the proportion of type I fibers and the number of RTF at 85% and 70% 1-RM in the leg press. However, they reported a significant interaction between capillary density and RTF achieved at 70% 1-RM (r = 0.7). Similar to other factors influencing fatigue resistance, there is evidence that certain exercise modes may promote an increase in capillary density, while others have been considered to reduce or maintain it along with hypertrophic adaptations of the skeletal muscle (MacInnis & Gibala, 2017; Tesch, 1988). Therefore, it could be argued that the strength-endurance relationship may be affected by an individual's quantitative and qualitative training history (i.e., the type and extent of past exercise experience). This hypothesis is supported by multiple investigations comparing the number of RTF at standardized relative loads between participants with strength- and endurance-dominant backgrounds (Desgorces et al., 2010; Panissa et al., 2013; Richens & Cleather, 2014).

In summary, there is evidence suggesting that the strength-endurance relationship may vary considerably among different exercise conditions and due to individual characteristics. However, since published models do not typically account for the contribution of these confounders, their practical applicability to make valid load predictions is still limited.

1.2.2.4 Proposing a solution to the problem

To improve the predictive accuracy of strength-endurance models, it seems crucial to account for the variance introduced by exercise- and subject-related confounders. This could be accomplished in two different ways. First, strength-endurance models could be complemented by adding essential confounders as covariates or moderator variables to the model, hence increasing the number of parameters and, thus, the complexity of the model. This strategy has been applied numerous times to improve strength-endurance-based 1-RM predictions, either: (i) by adding anthropometric variables and individual characteristics as predictors (Cummings & Finn, 1998; Kuramoto & Payne, 1995; Materko & Santos, 2009;

Whisenant et al., 2003), (ii) by combining load and RTF to an interaction term (Kravitz et al., 2003; Whisenant et al., 2003) or (iii) by using higher-order polynomials (Kemmler et al., 2006). However, each new predictor variable added to the model would require practitioners to record additional information before being able to make predictions. While some potential predictors could be easily determined (e.g., the type of exercise or biological sex), others would require a detailed assessment (e.g., anthropometric measures). In order to qualify for application in resistance training practice, such assessments would have to be time-efficient, easily quantifiable, and valid without requiring the acquisition of expensive technology. Unfortunately, this is not always the case.

A different solution to cope with exercise- and subject-related confounders would be to calculate relationships on an individual level in the form of a *strength-endurance profile*. That is, based on cross-sectional data of a single person in a specific exercise. This way, strength-endurance models would exclude any variance from between-subject or between-exercise factors. The idea of modeling cross-sectional performance on an individual level has been frequently pursued in exercise science and sports practice. Most notably, it has been applied for cycling and running performance in the context of critical power and critical speed (Pettitt, 2016; Vanhatalo et al., 2011), as well as velocity-based resistance training (Benavides-Ubric et al., 2020; García-Ramos et al., 2018; García-Ramos et al., 2019; Pérez-Castilla et al., 2022). As discussed in section 1.2.2.1, there have also been initial attempts to model the strength-endurance relationship based on the concept of critical power. However, *individualized* modeling is not without caveats. Most importantly, models are typically calculated from a limited number of data points, especially if the performance assessment cannot be repeated for multiple trials under homogeneous conditions (e.g., if the assessment accumulates fatigue). A low ratio between the number of observations and the number of model parameters typically yields larger fluctuations in parameter estimates across repeated samples due to the model being overfitted (Babyak, 2004). This fact is commonly overlooked or underappreciated in published research on individualized models of physical performance. Also, individualized models may build false certainty in model validity based on measures of model fit. For example, Arakelian et al. (2017) concluded that for the computation of the critical load model in the leg press exercise, a sample size of three observations (“work bouts”) was superior to four observations because it resulted in a higher R^2 value. Similarly, Dinyer, Byrd, Vesotsky, Succi, Clasey, and Bergstrom (2019) inferred the applicability of the critical power model to the deadlift exercise solely based on the R^2 statistics of individualized models calculated from four observations each. In a recent review, Bergstrom et al. (2021) even recommended that future investigations on the topic should report R^2 and SEE statistics for each individualized model.

In summary, modeling the strength-endurance relationship on an individual level for a specific exercise may improve the model's predictive accuracy and precision by eliminating variance resulting from exercise- or person-related confounders. However, it still needs to be determined if an approach of modeling strength-endurance on an individual level compromises predictive accuracy due to the limitations of small sample sizes.

1.3 Objectives of the dissertation project

The present thesis was designed to comprehensively investigate the idea of modeling strength endurance on an individual level. Research questions were defined and empirically evaluated to provide practitioners with an explicit directive for determining and implementing strength-endurance models as tools to guide programming in resistance training. All studies focused on the high-load range of the strength-endurance relationship (i.e., loads between 70% and 100% 1-RM), as this range was considered most relevant to strength & conditioning practitioners.

The following section will provide an overview of the three scientific articles associated with the current thesis and the research questions addressed by them.

Publication #1, entitled "*Modeling the Relationship between Load and Repetitions to Failure in Resistance Training: A Bayesian Analysis*", was designed to evaluate the validity of four commonly proposed model functions (i.e., model types) when applied to strength-endurance data at loads ranging from 70% to 100% 1-RM. Each function was fitted according to a complete-pooling structure and a multilevel structure to evaluate whether the strength-endurance relationship is indeed characterized by individual trends. The paper's primary purpose was to identify a modeling approach that provides a good fit and predictive accuracy while avoiding unnecessary model complexity.

The objective of **publication #2**, entitled "*Reproducibility of strength performance and strength-endurance profiles: A test-retest study*", was to investigate the robustness of the model functions addressed in publication #1 across test-retest trials. The paper further addresses the absolute and relative consistency of the test protocol applied in publications #1 and #2. The paper's primary purpose was to identify functions that yield stable parameter estimates over a short period of time when no, or only minimal, systematic changes are expected.

Finally, **publication #3**, entitled "*Data Collection for Strength-Endurance Profiles: Can Assessments Be Completed within a Single Session?*", compared two different approaches of data acquisition to evaluate whether the observations required for the computation of strength-endurance profiles should be taken from multiple training sessions (i.e., a multi-visit protocol, MV), or if they may be collected during a single session with prolonged rest periods in between trials (i.e., a single-visit protocol, SV). As a secondary objective, data from publication #3 were used to replicate the analysis of model functions presented in publication #1 to challenge the replicability of the most recent findings in a different sample.

2 Publications

2.1 Publication 1: Modeling the Relationship between Load and Repetitions to Failure in Resistance Training: A Bayesian Analysis

Authors:

Benedikt Mitter, Lei Zhang, Pascal Bauer, Arnold Baca and Harald Tschan

Publication status:

The article was published in the European Journal of Sport Science on June 30th, 2022 (Mitter, Zhang, et al., 2022).

DOI:

https://doi.org/10.1080/17461391.2022.2089915

Authors' contribution:

Benedikt Mitter: methodological conceptualization, project administration, data acquisition, data curation, data analysis, visualization, writing of the original draft

Lei Zhang: supervision during data analysis, writing of the original draft, proof-reading

Pascal Bauer: visualization, writing of the original draft, proof-reading

Arnold Baca: writing of the original draft, proof-reading

Harald Tschan: project supervision, methodological conceptualization, project administration, writing of the original draft, proof-reading

All authors listed above contributed to the present manuscript and approved the final version of it.

ABSTRACT

Purpose: To identify the relationship between load and the number of repetitions performed to momentary failure in the pin press exercise, the present study compared different statistical model types and structures using a Bayesian approach.

Methods: Thirty resistance-trained men and women were tested on two separate occasions. During the first visit, participants underwent assessment of their one-repetition maximum (1-RM) in the pin press exercise. On the second visit, they performed sets to momentary failure at 90%, 80% and 70% of their 1-RM in a fixed order during a single session. The relationship between relative load and repetitions performed to failure was fitted using linear regression, exponential regression and the critical load model. Each model was fitted according to the Bayesian framework in two ways: using an across-subjects pooled data structure and using a multilevel structure. Models were compared based on the variance explained (R^2) and leave-one-out cross-validation information criterion (LOOIC).

Results: Multilevel models, which incorporate higher-level commonalities into individual relationships, demonstrated a substantially better fit (R^2: 0.97 – 0.98) and better predictive accuracy compared to generalized pooled-data models (R^2: 0.89 – 0.93). The multilevel 2-parameter exponential regression emerged as the best representation of data in terms of model fit, predictive accuracy and model simplicity.

Conclusion: The relationship between load and repetitions performed to failure follows an individually expressed exponential trend in the pin press exercise. To accurately predict the load that is associated with a certain repetition maximum, the relationship should therefore be modeled on a subject-specific level.

Key Words (4-6): strength-endurance continuum; repetition maximum; maximum number of repetitions; prediction; critical load

1. INTRODUCTION

Modeling the relationship between exercise intensity and the maximum amount of realizable physical work has been an increasingly addressed objective in sports science (1). In resistance training, this relationship has previously been characterized by the term “strength-endurance continuum” (2) and can be described for a given exercise by modeling the external load as a function of the number of repetitions performed to momentary failure (RTF) (e.g., 3,4). Precise knowledge about the interrelation between these two variables can be beneficial in various ways. First, it would enable the comprehensive determination of a person's exercise-specific physical fatigability in dependence of the external load. In contrast to previously documented methods of assessing strength endurance (5), this approach may yield a descriptive indicator that is not limited to a single load, but rather describes fatigue resistance across a wide spectrum of loads (i.e., a "strength-endurance profile"). Second, it would enable the prediction of the maximum external load a person can move in a given exercise for any given number of repetitions. This involves the concept of estimating the one-repetition maximum (1-RM) based on the RTF that can be achieved at a submaximal load, which has been frequently investigated over the past decades (3,4,6–10). Third, it would enable certain methods of resistance training prescription, like the standardization of muscular exhaustion based on a predicted training maximum, a prescriptive approach which has been referred to as "relative intensity of set-repetition best" (11,12). Previous studies that intended to model the relationship between external load and RTF mainly focused on applying across-subject regressions by means of either linear (3,7,13,14) or exponential models (3,4,15,16). However, there is evidence suggesting that the strength-endurance relationship may succumb to considerable interindividual differences attributed to numerous factors, such as specificity to the tested exercise (3,17), movement cadence (15,18) as well as the athletes' training experience (6,10,17) and training background (16,19). Considering these potential confounders, one could argue that any statistical modeling approach that generalizes the relationship across different subjects without accounting for subject heterogeneity (i.e., "complete-pooling models") may result in a suboptimal representation of the strength-endurance relationship, therefore impeding both the fit and predictive accuracy of such models. Indeed, independent validation studies predominantly reported noticeable inaccuracy of 1-RM predictions based on complete-pooling models, especially when using lower relative loads (3,8–10,20). Several researchers have sought to overcome this issue and improve model validity by transposing the concept of critical power (21) to dynamic resistance training (1,22). The so-called *critical load* model, also referred to as critical lift or critical resistance model, introduced the idea of modeling strength endurance on an individual level (i.e., "no-pooling models") rather than a group-level, therefore treating the individual as the population of interest. While this concept may provide a valuable alternative for when data availability is limited, it should still be treated with caution in scientific research, since it implies a higher potential to overfit data (23). A more promising solution may be expected by applying a multilevel model (i.e., "mixed model", also called "hierarchical model" or "partial pooling model") to the strength-endurance relationship, including both, group-level and subject-level parameters (23). In particular, the use of Bayesian multilevel modeling seems promising, as simulation research has shown Bayesian parameter estimation to be more accurate than maximum likelihood estimation in small samples (24). However, it has yet to be evaluated whether a multilevel modeling approach yields an advantage over the complete-pooling approach that has been primarily applied in research thus far. Furthermore, proposed models (linear regression, exponential regression, and critical load model) have yet to be compared among each other to determine which one provides the most appropriate representation of the strength-endurance relationship. The present study was designed to address these two issues using the example of the pin press exercise, which can be considered a variant of the bench press, in a resistance-trained population. Results will help to improve understanding of the relationship between load and RTF across a high-load range.

2. MATERIALS AND METHODS

2.1 Participants

Nineteen men and eleven women with previous experience in resistance training voluntarily participated in the investigation. Descriptive characteristics of participants are summarized in Table 1. Inclusion criteria were: (a) being free of illness and injury, (b) being between 18 and 40 years of age, (c) having at least one year of regular training experience in the bench press exercise and (d) achieving a minimal relative 1-RM in the pin press of 1x body mass (men) or 0.75x body mass (women). Subjects were informed about benefits and potential risks related to their participation, completed a modified Physical Activity Readiness Questionnaire and signed an informed consent form prior to undergoing any test. All procedures were implemented in accordance with the ethical guidelines of the Declaration of Helsinki and approved by a local ethical review committee (no. 00461).

2.2 Experimental design

Participants attended the laboratory on two days, separated by approximately 48 hours. On day 1, subjects were assessed for body mass and height using a scale (Seca Model 877; SECA GmbH & Co. KG., Hamburg, Germany) and stadiometer (Seca Model 217; SECA GmbH&Co. KG., Hamburg, Germany). Afterwards, they were familiarized with the execution of the free-weight pin press exercise and followed a progressive loading test to determine their individual 1-RM. On day 2, participants completed sets to momentary failure at submaximal loads in descending order. Subjects were instructed to refrain from strenuous exercise and alcohol 24 hours before tests and not to consume caffeine 6 hours prior to testing. The exercise was performed in a Competition Combo Rack approved by the International Powerlifting Federation using a 20-kg barbell and calibrated weight plates (Eleiko, Halmstad, Sweden).

Table 1. Subject characteristics

	Male (n=19)	**Female (n=11)**
Age (y)	27.4 ± 3.7 [21.2 - 33.6]	26.9 ± 5.2 [20.2 - 35.9]
Experience in BP (y)	7.6 ± 3.0 [3.0 - 15.0]	3.5 ± 2.6 [1.0 - 10.0]
Height (cm)	180.9 ± 5.4 [171.5 - 191.6]	163.1 ± 5.1 [154.3 - 171.0]
Body mass (kg)	85.4 ± 7.2 [69.2 - 96.9]	63.4 ± 4.4 [55.2 - 69.7]
1-RM (kg)	112.2 ± 13.6 [85.0 - 142.5]	61.4 ± 10.0 [50.0 - 80.0]
Relative 1-RM (kg・kg^{-1})	1.32 ± 0.12 [1.15 - 1.50]	0.98 ± 0.19 [0.77 - 1.31]
RTF at 90%1-RM (n)	4.3 ± 0.9 [3.0 - 6.0]	4.3 ± 1.3 [2.0 - 6.0]
RTF at 80%1-RM (n)	7.6 ± 1.3 [5.0 - 10.0]	8.4 ± 1.6 [6.0 - 11.0]
RTF at 70%1-RM (n)	12.1 ± 2.4 [7.0 - 16.0]	13.1 ± 2.1 [9.0 - 15.0]

Data are presented as mean ± SD [min - max].
BP, bench press; 1-RM, one-repetition maximum in the pin press; RTF, repetitions performed to momentary failure in the pin press.

To provide participants a safe testing environment for performing sets to momentary failure and to reduce potential variability in RTF resulting from an inconsistent use of the stretch-shortening cycle, the pin press was executed according to the following movement specifications: in each repetition, subjects were required to lower the barbell onto two safety pins adjusted to a height that would allow for a distance between the barbell's lowest position and the participant's chest of up to 3 cm. Upon having the barbell come to rest on the safety pins, a researcher would provide the command "Press!", ordering the subject to perform the concentric phase of the movement at maximum intended velocity until reaching full extension of their elbows. When multiple repetitions were executed within a set performed to momentary failure, participants were further instructed to autonomously minimize the time holding the barbell with extended elbows in between repetitions in order to reach the point of momentary failure as quickly as possible. Throughout each set, they had to maintain their feet's position on the floor and keep their hip, shoulders and head in contact with the bench.

A linear position transducer (GymAware Power Tool, Kinetic Performance Technologies, Canberra, Australia) was used to record mean concentric barbell velocity, to provide testers with feedback during the 1-RM assessment and help selecting appropriate load increments. The accuracy of the device has been scientifically validated before (25) and its use for the assessment of mean velocity has been reported to provide good test-retest reliability (26,27).

2.3 One-repetition maximum assessment (day 1)

Participants followed a standardized general warm-up including 5 min of stationary cycling (Kettler X1, Trisport, Huenenberg, Switzerland) at a cadence of about 80 rpm and a constant power output of 1 W per kg body mass. Subsequently they completed 2 min of unloaded dynamic mobilization exercises comprising circumduction of the shoulders, flexion and extension of the elbows and circumduction of the wrists, followed by 10 repetitions of axial external rotation of the humerus against light elastic resistance. In the next step, subjects were required to estimate their 1-RM in the pin press, considering the previously described specifications for movement execution. A progressive loading scheme was applied to slowly approach the true 1-RM, using loads equivalent to 25%, 50%, 75%, 85% and 95% of the estimated 1-RM. The number of repetitions performed at each load and passive rest in between sets were standardized according to an established autoregulatory procedure (25,28) that bases set configurations on the achieved barbell velocity of the preceding set, which has been considered a good predictor of the actually applied relative load (29). The rationale for employing this autoregulatory approach was to rudimentarily account for the possibility of subjects under- or overestimating their 1-RM and, consequently, being assigned an inadequate combination of actual warm-up loads, repetition numbers and rest periods that might result when assigning fixed values to inaccurate subjective estimates. Participants initially performed three repetitions with a 3 min break in between sets. Volume was adapted to two repetitions accompanied by a 4 min break, once mean velocity dropped below 1.0 $m \cdot s^{-1}$, and further reduced to a single repetition accompanied by 5 min of rest, once mean velocity fell below 0.65 $m \cdot s^{-1}$. Rest intervals were chosen corresponding to those reported for highly reliable 1-RM test protocols (30). After completing 95% of their estimated 1-RM, load increments were selected individually based on the participant's subjective feedback and achieved mean barbell velocity. Larger individual load increments of 2.5 to 10 kg were selected as long as the achieved mean concentric barbell velocity of the preceding attempt was above 0.2 $m \cdot s^{-1}$, which corresponds to recently reported norm values (mean + one standard deviation) of the velocity achieved at the 1-RM in the bench press (29). Small load increments of 2.5 kg were selected once mean concentric barbell velocity fell below

0.2 m·s^{-1}. The test was terminated once a subject could no longer press an assigned load across the full range of motion, suggesting that the 1-RM had been reached. On average, subjects required 2.5 ± 1.4 attempts to determine their 1-RM and reached a velocity at 1-RM of 0.13 ± 0.04 m·s^{-1}.

2.4 Repetitions to failure assessment (day 2)

Participants were tested for the RTF in the pin press at loads corresponding to 90%, 80% and 70% of the previously determined 1-RM. Each RTF test was initiated by the same general warm-up applied for the 1-RM assessment on day 1. Subsequently, subjects completed three specific warm-up sets in the pin press, comprising three repetitions at 25%, three repetitions at 50% and two repetitions at 75% 1-RM. 3 min of rest were provided in between warm-up sets and 5 min of rest prior to each test to momentary failure. A test to momentary failure was terminated once the participant attempted to complete the concentric phase of a current repetition, but was unable to do so (31). To increase efficiency of data acquisition and, thus, limit participant drop out, the test protocol for the RTF assessment was designed for implementation within a single visit. Therefore, two methodological specifications were applied in order to minimize negative effects of accumulating fatigue on the completed RTF. First, the sequence of tested loads was fixed in a declining manner (i.e. set 1: 90%, set 2: 80%, set 3: 70% 1-RM), as research suggests that fatigue is more prevalent after sets performed to failure at lighter loads compared to heavier loads (32). Second, subjects were granted a prolonged period of rest in between sets to failure (33). For this purpose, each set to momentary failure was immediately followed by 5 min of passive rest. After that, subjects completed the general and specific warm-up described above in order maintain positive warm-up effects. This yielded an approximate 22 min in between sets to failure, while applying the same preparatory measures before each test.

2.5 Statistical modeling

The following four model types were used to quantify the relationship between load (expressed as a percentage of the 1-RM) as the dependent variable, and RTF as the independent variable:

Lin: $load \sim Normal\ (\boldsymbol{a} + \boldsymbol{b} \cdot RTF, \sigma^2)$ [1]

Ex2: $load \sim Normal\ (\boldsymbol{a} \cdot e^{(\boldsymbol{b}\, \cdot\, RTF)}, \sigma^2)$ [2]

Ex3: $load \sim Normal\ \left(\boldsymbol{c} + \boldsymbol{a} \cdot e^{(\boldsymbol{b}\, \cdot\, RTF)}, \sigma^2\right)$ [3]

Crit: $load \sim Normal\ (\boldsymbol{L'}/(RTF - \boldsymbol{k}) + \boldsymbol{CL}, \sigma^2)$ [4]

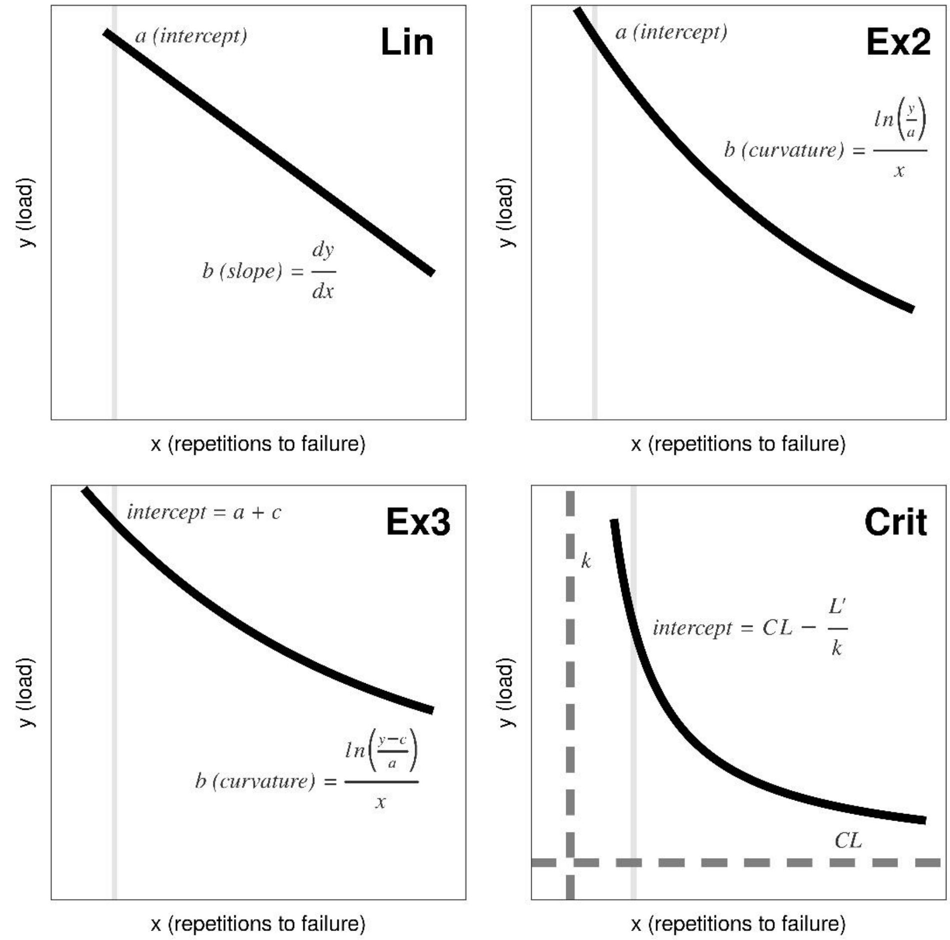

Figure 1. Illustrative examples of the investigated model types and description of model parameters. Solid black lines display model functions (extended slightly below 0); solid grey lines display the y-axis at x=0; dashed grey lines display the vertical (k) and horizontal asymptote (CL) of the critical load model; intercepts mark the intersection of the model function and the y-axis at x=0; Lin, linear regression model; Ex2, exponential 2-parameter regression model; Ex3, exponential 3-parameter regression model; Crit, critical load model.

The linear model (*Lin*, equation 1) describes the relationship as a simple 2-parameter linear regression, which has been assumed to be a convenient approximation at a high-load range (3,7,13,14). The model contains an additive intercept parameter ***a*** and a slope coefficient ***b***. The exponential regression model (*Ex2*, equation 2, and *Ex3*, equation 3) describes a curvilinear relationship between variables. Previous research predominantly advocated exponential models in the form of equation 3, featuring a multiplicative parameter ***a***, an exponential curvature parameter ***b*** and an additive parameter ***c*** (3,4,15,16). However, we also included equation 2 as a simplified version of equation 3 that omits the additive parameter ***c*** (8). Ultimately, equation 2 can be rearranged to a simple linear regression model by applying a natural log transformation to the dependent variable, making the model easily computable. Finally, the critical load model (*Crit*, equation 4) entails a hyperbolic relationship between the variables (1,22). The model comprises a curvature parameter ***L'***, a vertical asymptote parameter ***k*** and a horizontal asymptote parameter ***CL***. An illustrative description of model functions is provided in Figure 1.

2.6 Model fitting

Each model type (equations 1 to 4) was fitted according to two different model structures: first, a complete-pooling model (CPM) was calculated, including all data and containing only fixed effects, therefore not accounting for interindividual differences. Second, a multilevel model (MLM) was calculated, which, in addition to fixed effects, also added random effects for each subject. This implies that for the multilevel models, every subject-level parameter was fitted to the data of a single participant, assuming a higher-level group distribution of the respective parameter. For instance, it was assumed that a generic subject-level parameter "x" was drawn from a group-level normal distribution with the mean "μ_x" and variance "σ_x^2", namely, x ~ *Normal* (μ_x, σ_x^2). The possibility of correlated parameter structures within every multilevel model was accounted for by introducing a covariance matrix for the respective model's subject-level parameters. Therefore, eight different models were fitted that differed in model type (*Lin*, *Ex2*, *Ex3*, *Crit*) and structure (CPM, MLM).

Data analysis was conducted following a Bayesian approach, using the probabilistic programming language Stan (34), version 2.21.0, to estimate parameter distributions. Weakly informative priors were selected for variance parameters and the covariance matrix. Priors for the group-level parameters (fixed effects) of each model were defined by moment-matching a normal distribution to the posteriors of a preceding pilot study done on a separate sample of eight subjects. A prior sensitivity analysis was conducted to identify an appropriate scaling factor that would mitigate the influence of priors on posterior distributions, thus ensuring that pilot-derived priors were minimally informative. Further details on the pilot sample, prior selection and the sensitivity analysis are provided online (Supplemental digital material 1). Furthermore, sampling details and Stan codes are available online to enhance analytical reproducibility (Supplemental digital material 2).

2.7 Model evaluation

Models were compared in terms of model fit and model predictive accuracy. The model fit was analyzed by calculating a Bayesian R^2 distribution (35) and interpreted according to the Maximum a Posteriori estimate (MAP) and the 90% Highest Density Interval (HDI) (36). Differences between R^2 posterior distributions were analyzed and interpreted according to their probability density overlap ($\cap R^2$) and deemed "substantial" for $\cap R^2 \leq 5\%$. Model predictive accuracy was evaluated by calculating the expected log predictive density and converting it into a measure of deviance labelled LOOIC (37), whereas smaller values of LOOIC indicate higher predictive validity. Differences in LOOIC between models (ΔLOOIC) were complemented with an estimated standard error of difference (SE) (37) and considered to be substantial if they exceeded 4x the SE. In cases of model comparisons not indicating substantial differences in model fit or predictive accuracy, models were further evaluated according to their simplicity. Under respective circumstances, the logical principle of Occam's razor advocates that models with fewer parameters should be considered as more efficient. Posterior analysis was completed using R version 4.0.5 and the R packages *bayestestR* and *loo*.

3. RESULTS

In all cases, the multilevel model resulted in a substantially better model fit compared to their complete-pooling counterpart ($\cap R^2 < 0.1\%$ for all comparisons). Ex3 provided the highest R^2 among complete-pooling models, being substantially different from Lin ($\cap R^2 < 0.1\%$), but not from Ex2 ($\cap R^2 = 6.5\%$) and Crit ($\cap R^2 = 88.5\%$). The multilevel variant of Crit showed the best overall model fit, albeit not being substantially different from other multilevel models ($\cap R^2 = 13.6 - 90.6\%$). Posterior distributions for R^2 are displayed in Figure 2. Every multilevel model further provided a substantially higher predictive accuracy when compared to its complete-pooling counterpart. Ex3 resulted in the lowest LOOIC among complete-pooling models, indicating a substantial difference from Lin (ΔLOOIC ± SE = 49.5 ± 9.5), but not from Ex2 (ΔLOOIC ± SE = 26.6 ± 7.0) and Crit (ΔLOOIC ± SE = 1.9 ± 1.5). Across multilevel models, Ex3 provided the highest predictive accuracy, although LOOIC was not substantially different from Lin (ΔLOOIC ± SE = 41.8 ± 14.4), Ex2 (ΔLOOIC ± SE = 2.7 ± 7.8) and

Crit (ΔLOOIC ± SE = 6.5 ± 2.2). Overall, the multilevel variant of Ex2 emerged the most efficient model (Figure 3) due to its distinct similarity to the multilevel variants of Ex3 and Crit in terms of model fit and predictive accuracy, while relying on fewer parameters. Furthermore, it yielded substantially better predictive accuracy (ΔLOOIC ± SE = 39.0 ± 7.4) compared to the multilevel variant of Lin. Statistics for model evaluation are summarized in Table 2.

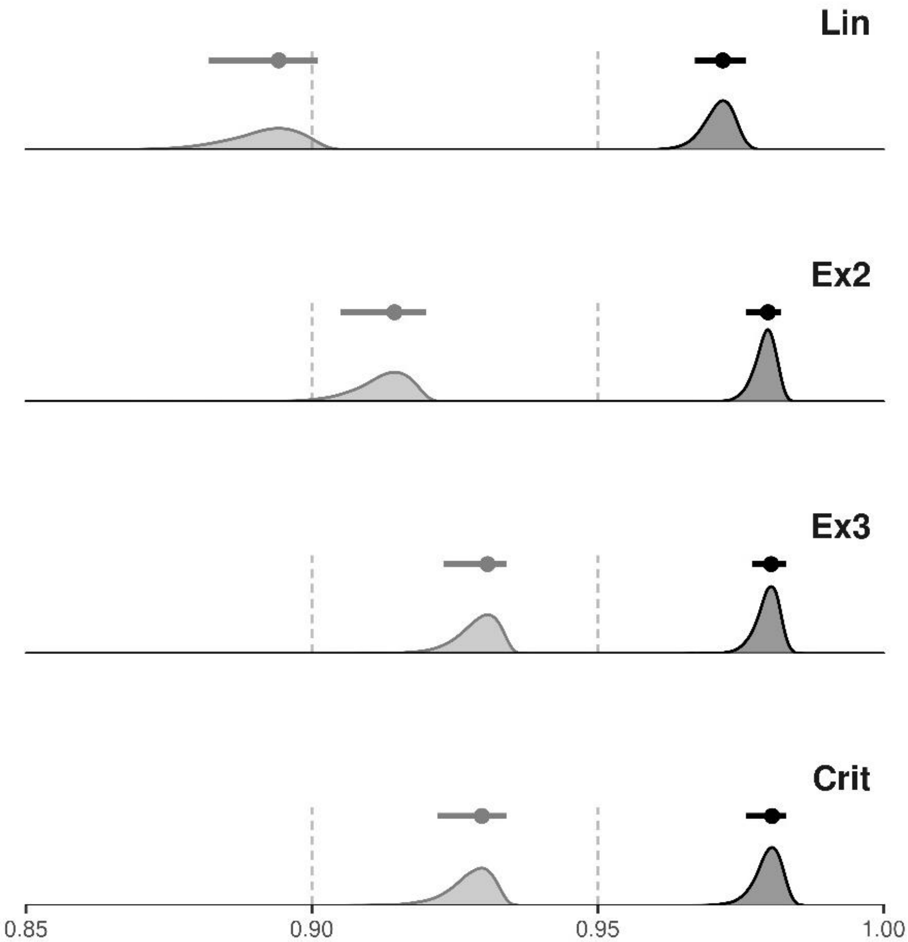

Figure 2. Comparison of model fit (R^2 posterior distributions). Dark grey distributions illustrate multilevel models; light grey distributions illustrate complete-pooling models; points represent maximum a posteriori (MAP) estimates; error bars display 90% highest density intervals (HDIs). Lin, linear regression model; Ex2, exponential 2-parameter regression model; Ex3, exponential 3-parameter regression model; Crit, critical load model.

Table 2. Comparison of 8 models, ranked from best to worst model performance

Rank	Model	n_P_g (n_P_s)	ΔLOOIC	SE	R^2 MAP [90% HDI]
1	Ex2 [MLM]	2 (60)	0.0	0.0	0.980 [0.976; 0.982]
2	Ex3 [MLM]	3 (90)	-2.7	8.0	0.980 [0.977; 0.983]
3	Crit [MLM]	3 (90)	3.8	7.3	0.981 [0.976; 0.983]
4	Lin [MLM]	2 (60)	39.0*	7.4	0.972 [0.967; 0.976]
5	Ex3 [CPM]	3 (0)	104.4*	17.7	0.931 [0.923; 0.934]
6	Crit [CPM]	3 (0)	106.3*	17.8	0.930 [0.922; 0.934]
7	Ex2 [CPM]	2 (0)	131.0*	18.0	0.915 [0.905; 0.920]
8	Lin [CPM]	2 (0)	153.9*	16.9	0.894 [0.882; 0.901]

Models are ranked according to their fit, predictive accuracy and simplicity.
n_P_g, number of group level parameters (fixed effects); n_P_s, number of subject level parameters (random effects); ΔLOOIC, difference in LOOIC compared to the most efficient model Ex2 [MLM] (lower values indicating better predictive performance, * indicating a substantial difference); SE, standard error of the difference in LOOIC; R^2, variance explained; MAP, Maximum a Posteriori estimate; HDI, Highest Density Interval.
Ex2, exponential 2-parameter regression model; Ex3, exponential 3-parameter regression model; Crit, critical load model; Lin, linear regression model; MLM, multilevel structure; CPM, complete-pooling structure.

Posterior distributions of group-level parameters (fixed effects) and subject-level parameters (random effects) calculated for the multilevel *Ex2* model are displayed in Figure 4. Group-level parameters were estimated at 102.76 (90% HDI = [102.24, 103.29]) for the intercept ***a*** and at -0.032 (90% HDI = [-0.034, -0.030]) for the curvature parameter ***b***. Subject-level parameters yielded homogeneous estimates for the intercept (between-subject coefficient of variation [90% HDI] = 0.1% [0.0, 0.9]), but considerable variance for the curvature parameter (between-subject coefficient of variation [90% HDI] = 19.7% [15.4, 25.9]).

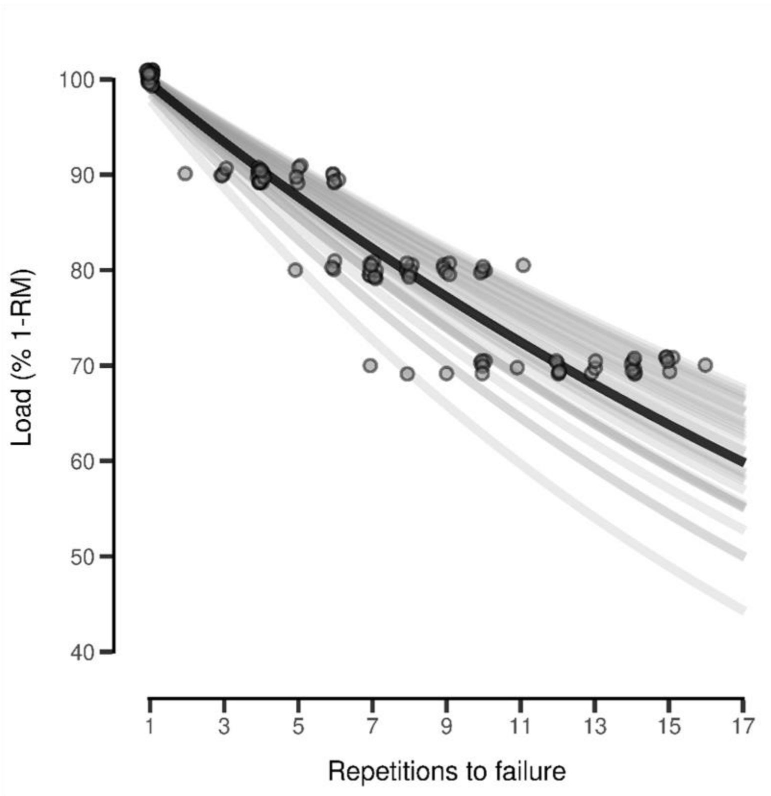

Figure 3. The strength-endurance relationship represented by the multilevel 2-parameter exponential regression model. Points represent subject data (jittered illustration); solid black line displays the group-level model; grey lines display subject-level models. 1-RM, one-repetition maximum.

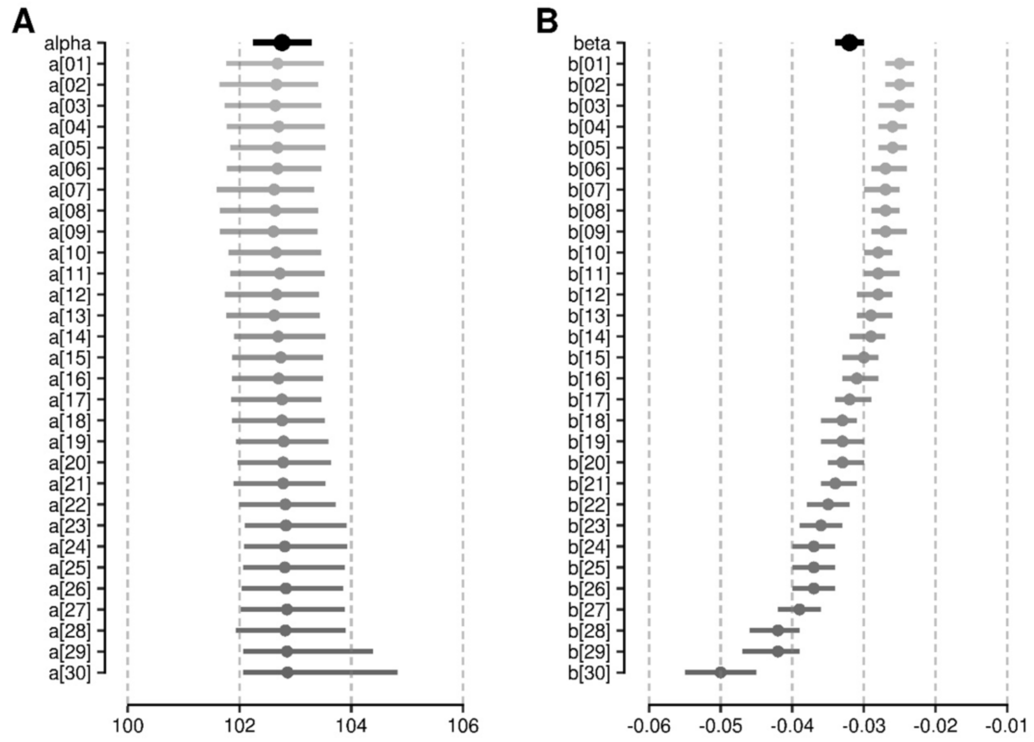

Figure 4. Posterior summary of the multilevel 2-parameter exponential regression model, including the intercept ***a*** (panel A) and curvature parameters ***b*** (panel B). Points represent maximum a posteriori (MAP) estimates; error bars display 90% highest density intervals [HDI]. Alpha, group-level parameter (fixed effect); a[i], individual-level parameter (random effect) of subject *i*.

4. DISCUSSION

The objective of the present study was to investigate the relationship between external load and the RTF in the pin press exercise. In contrast to the greater part of published research on the topic, we did not confine our analysis to a single proposed model, but rather included several previously documented models to address two major issues: first, we aimed to determine whether a modeling approach that expresses individual relationships with higher-level commonalities (i.e. a multilevel model structure) offers substantial advantages in comparison to the traditional modeling approach that pools data without differentiation between subjects. Second, we compared four different models (equations 1 to 4) to identify which one provides the best approximation to the relationship in terms of model fit and predictive accuracy. Analysis was conducted using a sampling-based Bayesian method, which is considered helpful in situations with relatively small samples (24). In addition, Bayesian methods allow the inclusion of prior information into the parameter estimation process, which may be beneficial to a priori rule out improbable values, given that adequate prior knowledge about parameters is available. Our findings yield further insight into latent structures of the strength-endurance continuum and provide practitioners with a novel and more accurate approach to calculate loads corresponding to a given repetition maximum.

4.1 Multilevel vs. complete-pooling models

To the best of our knowledge, this was the first investigation to compare pooled data modeling on the relationship between relative load and the RTF to a multilevel approach that specifies parameter expressions on an individual level. Complete-pooling model structures demonstrated both, a worse model fit and lower predictive accuracy compared to multilevel model structures, which may be attributed to noticeable variance of the RTF at lower relative loads (Figure 4). These results support the assumption that traditionally communicated models deploying only group-level parameters (e.g., 3,4,7,14–16) do not sufficiently account for interindividual variation in the RTF that can be performed at a given relative load. Practitioners who apply respective models drawn from literature should be conscious of a potential estimation error, especially at lighter loads. Improved predictive accuracy can be expected by modeling the relationship between load and RTF on an individual level based on subject-specific data. However, application of this concept requires practitioners to assess the RTF at multiple different loads under comparable psycho-physiological conditions.

4.2 Linear vs. exponential vs. critical load models

Based upon our findings, the strength-endurance continuum appears to follow a curvilinear trend at loads of 70% 1-RM and higher, which can be modeled effectively using an exponential regression or the critical load model. The results are in accordance with earlier publications comparing linear to 3-parameter exponential regression models, whereas authors reported a better across-subject fit for the nonlinear model, as indicated by the variance explained (R^2) and standard error of estimate (3,16). In the present study, the 3-parameter exponential model (equation 3), that has been previously proposed on numerous occasions (3,4,15,16) showed a slightly better model fit and predictive accuracy than its 2-parameter alternative (equation 2) for the pooled-data fit, although the difference was not deemed substantial. In case of the multilevel fit, equation 2 resulted in exceptionally similar estimates of R^2 and LOOIC. Despite our analysis not showing a statistical advantage of the 2-parameter exponential regression model, it exceeds both the 3-parameter exponential regression model and the critical load model in terms of simplicity, as indicated by the number of model parameters. Therefore, we endorse that applying the 2-parameter exponential regression model to subject-specific data yields the best representation of a person's strength-endurance relationship, without adding unnecessary complexity to the model.

4.3 Parameter analysis

Subject-level intercepts of the 2-parameter exponential regression model (parameter ***a*** in equation 2) only showed a small deviation from the group-level parameter, which may be attributed to load being normalized to the individual 1-RM. However, the curvature parameter (***b*** in equation 2) showed considerable variation between subjects, suggesting that it may constitute the main influence on the individual manifestation of the strength-endurance relationship. Therefore, future studies should consider employing a comprehensive analysis on potential confounders that may affect estimates of the curvature parameter. While an additional evaluation of model parameters was beyond the scope of the present study, an exploratory analysis of subject characteristics and their effect on subject-level parameters is provided online for interested readers (Supplemental digital material 3).

4.4 Limitations

Readers should consider that the present study investigated the strength-endurance relationship only in the specific case of the pin press using a highly controlled exercise technique without standardizing movement cadence. Hence, the multilevel 2-parameter exponential regression may not necessarily provide the best approximation for other exercises that follow a different distribution of the RTF across loads, which questions the transferability of the present findings to a standard touch-and-go bench press. Additionally, our findings only cover for relative loads of 70% 1-RM and above, therefore neglecting model validity at lower loads. Finally, models were calculated based on data acquired during two visits, whereas tests to momentary failure were exclusively conducted during the second visit without randomizing the order of tests. Therefore, the possibility of an order effect influencing the acquired data cannot be ruled out. While a similar approach to single-visit testing with a fixed order of trials has recently been proposed for the valid assessment of critical power (38), our data provide no conclusion whether subjects truly initiated each set to momentary failure under fully rested conditions. Future research should therefore target two important objectives: first, different methodological approaches of assessing RTF at multiple loads should be compared and it should be evaluated how they influence the estimated strength-endurance relationship on a subject-level (e.g., effects of single-visit vs. multiple-visit data acquisition). Second, the multilevel relationship between load and RTF should be investigated using a variety of exercises with less restrictive movement specifications, including the touch-and-go bench press.

5. **CONCLUSION**

The present study supplies evidence that the strength-endurance continuum, described by the relationship between relative load and the number of repetitions performed to failure, displays substantial interindividual variation. Practitioners and researchers can address this issue by modeling the relationship on an individual level, whereas the 2-parameter exponential regression evidently constitutes the most efficient model for this purpose in the pin press exercise.

CONFLICT OF INTEREST AND FUNDING

In accordance with Taylor & Francis policy and our ethical obligation as researchers, the authors declare no financial or personal relationship with any of the mentioned companies or brands, therefore having no conflict of interest. No funding was received for conducting this study.

REFERENCES

1. Bergstrom HC, Dinyer TK, Succi PJ, Voskuil CC, Housh TJ. Applications of the Critical Power Model to Dynamic Constant External Resistance Exercise: A Brief Review of the Critical Load Test. Sports (Basel). 2021;9(2):15.
2. Campos GER, Luecke TJ, Wendeln HK, Toma K, Hagerman FC, Murray TF, Ragg KE, Ratamess NA, Kraemer WJ, Staron RS. Muscular adaptations in response to three different resistance-training regimens: specificity of repetition maximum training zones. Eur J Appl Physiol. 2002;88(1-2):50–60.
3. Reynolds JM, Gordon TJ, Robergs RA. Prediction of One Repetition Maximum Strength from Multiple Repetition Maximum Testing and Anthropometry. J Strength Cond Res. 2006;20(3):584–92.
4. Mayhew JL, Ball TE, Arnold MD, Bowen JC. Relative Muscular Endurance Performance as a Predictor of Bench Press Strength in College Men and Women. J Strength Cond Res. 1992;6(4):200–6.
5. Lawton TW, Cronin JB, McGuigan MR. Strength testing and training of rowers: a review. Sports Med. 2011;41(5):413–32.
6. Braith RW, Graves JE, Leggett SH, Pollock ML. Effect of training on the relationship between maximal and submaximal strength. Med Sci Sports Exerc. 1993;25(1):132–8.
7. Brzycki M. Strength Testing - Predicting a One-Rep Max from Reps-to-Fatigue. JOPERD. 1993;64(1):88–90.
8. Mayhew JL, Johnson BD, Lamonte MJ, Lauber D, Kemmler W. Accuracy of prediction equations for determining one repetition maximum bench press in women before and after resistance training. J Strength Cond Res. 2008;22(5):1570–7.
9. LeSuer DA, McCormick JH, Mayhew JL, Wasserstein RL, Arnold MD. The Accuracy of Prediction Equations for Estimating 1-RM Performance in the Bench Press, Squat, and Deadlift. J Strength Cond Res. 1997;11(4):211–3.
10. Brechue WF, Mayhew JL. Upper-body work capacity and 1RM prediction are unaltered by increasing muscular strength in college football players. J Strength Cond Res. 2009;23(9):2477–86.
11. Scott BR, Duthie GM, Thornton HR, Dascombe BJ. Training Monitoring for Resistance Exercise: Theory and Applications. Sports Med. 2016;46(5):687–98.
12. Suchomel TJ, Nimphius S, Bellon CR, Hornsby WG, Stone MH. Training for Muscular Strength: Methods for Monitoring and Adjusting Training Intensity. Sports Med. 2021;51(10):2051–66.

13. Haff G, Triplett NT, editors. Essentials of strength training and conditioning. Champaign IL: Human Kinetics; 2016. 735 p.
14. Adams GM, Beam WC. Exercise physiology laboratory manual. New York NY: McGraw-Hill; 2014. 338 p.
15. Sakamoto A, Sinclair PJ. Effect of movement velocity on the relationship between training load and the number of repetitions of bench press. J Strength Cond Res. 2006;20(3):523–7.
16. Desgorces FD, Berthelot G, Dietrich G, Testa MSA. Local muscular endurance and prediction of 1 repetition maximum for bench in 4 athletic populations. J Strength Cond Res. 2010;24(2):394–400.
17. Hoeger WW, Hopkins DR, Barette SL, Hale DF. Relationship between repetitions and selected percentages of one repetition maximum: A comparison between un-trained and trained males and females. J Strength Cond Res. 1990;4(2):47–54.
18. LaChance PF, Hortobagyi T. Influence of Cadence on Muscular Performance During Push-up and Pull-up Exercise. J Strength Cond Res. 1994;8(2):76–9.
19. Richens B, Cleather DJ. The relationship between the number of repetitions performed at given intensities is different in endurance and strength trained athletes. Biol Sport. 2014;31(2):157–61.
20. Ware JS, Clemens CT, Mayhew JL, Johnston TJ. Muscular endurance repetitions to predict bench press and squat strength in college football players. J Strength Cond Res. 1995;9(2):99–103.
21. Burnley M, Jones AM. Power–duration relationship: Physiology, fatigue, and the limits of human performance. Eur J Sport Sci. 2018;18(1):1–12.
22. Morton RH, Redstone MD, Laing DJ. The Critical Power Concept and Bench Press: Modeling 1RM and Repetitions to Failure. Int J Exerc Sci. 2014;7(2):152–60.
23. Gelman A. Multilevel (Hierarchical) Modeling: What It Can and Cannot Do. Technometrics. 2006;48(3):432–5.
24. Lee S-Y, Song X-Y. Evaluation of the Bayesian and Maximum Likelihood Approaches in Analyzing Structural Equation Models with Small Sample Sizes. Multivariate Behav Res. 2004;39(4):653–86.
25. Mitter B, Hölbling D, Bauer P, Stöckl M, Baca A, Tschan H. Concurrent Validity of Field-Based Diagnostic Technology Monitoring Movement Velocity in Powerlifting Exercises. J Strength Cond Res. 2021;35(8):2170–8.
26. Dorrell HF, Moore JM, Smith MF, Gee TI. Validity and reliability of a linear positional transducer across commonly practised resistance training exercises. J Sports Sci. 2019;37(1):67–73.

27. Orange ST, Metcalfe JW, Marshall P, Vince RV, Madden LA, Liefeith A. Test-Retest Reliability of a Commercial Linear Position Transducer (GymAware PowerTool) to Measure Velocity and Power in the Back Squat and Bench Press. J Strength Cond Res. 2020;34(3):728–37.
28. Sánchez-Medina L, Perez CE, Gonzalez-Badillo JJ. Importance of the propulsive phase in strength assessment. Int J Sports Med. 2010;31(2):123–9.
29. Weakley J, Mann B, Banyard HG, McLaren S, Scott T, Garcia-Ramos A. Velocity-Based Training: From Theory to Application. Strength Cond J. 2021;43(2):31–49.
30. Grgic J, Lazinica B, Schoenfeld BJ, Pedisic Z. Test-Retest Reliability of the One-Repetition Maximum (1RM) Strength Assessment: a Systematic Review. Sports Med Open. 2020;6(1):31.
31. Steele J, Fisher J, Giessing J, Gentil P. Clarity in reporting terminology and definitions of set endpoints in resistance training. Muscle Nerve. 2017;56(3):368–74.
32. Sánchez-Medina L, González-Badillo JJ. Velocity loss as an indicator of neuromuscular fatigue during resistance training. Med Sci Sports Exerc. 2011;43(9):1725–34.
33. Salles BF de, Simão R, Miranda F, Da Novaes JS, Lemos A, Willardson JM. Rest interval between sets in strength training. Sports Med. 2009;39(9):765–77.
34. Carpenter B, Gelman A, Hoffman MD, Lee D, Goodrich B, Betancourt M, Brubaker M, Guo J, Li P, Riddell A. Stan: A Probabilistic Programming Language. J. Stat. Soft. 2017;76(1):32.
35. Gelman A, Goodrich B, Gabry J, Vehtari A. R-squared for Bayesian Regression Models. Am Stat. 2019;73(3):307–9.
36. Makowski D, Ben-Shachar M, Lüdecke D. bayestestR: Describing Effects and their Uncertainty, Existence and Significance within the Bayesian Framework. JOSS. 2019;4(40):1541.
37. Vehtari A, Gelman A, Gabry J. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat Comput. 2017;27(5):1413–32.
38. Triska C, Hopker J, Wessner B, Reif A, Tschan H, Karsten B. A 30-Min Rest Protocol Does Not Affect W', Critical Power, and Systemic Response. Med Sci Sports Exerc. 2021;53(2):404–12.

APPENDICES

Supplemental digital material 1.pdf (Prior summary)

Supplemental digital material 2.pdf (Computational details)

Supplemental digital material 3.pdf (Exploratory model analysis)

The supplemental material can be downloaded using the following link:

https://www.tandfonline.com/doi/suppl/10.1080/17461391.2022.2089915

2.2 Publication 2: Reproducibility of strength performance and strength-endurance profiles: A test-retest study

Authors:

Benedikt Mitter, Robert Csapo, Pascal Bauer and Harald Tschan

Publication status:

The article was published in the European Journal of Sport Science on May 5th, 2022 (Mitter, Csapo, et al., 2022).

DOI:

https://doi.org/10.1371/journal.pone.0268074

Authors' contribution:

Benedikt Mitter: methodological conceptualization, project administration, data acquisition, data curation, data analysis, visualization, app conceptualization & development, writing of the original draft

Robert Csapo: app conceptualization, writing of the original draft, proof-reading

Pascal Bauer: visualization, writing of the original draft, proof-reading

Harald Tschan: project supervision, methodological conceptualization, project administration, writing of the original draft, proof-reading

All authors listed above contributed to the present manuscript and approved the final version of it.

ABSTRACT

The present study was designed to evaluate the test-retest consistency of repetition maximum tests at standardized relative loads and determine the robustness of strength-endurance profiles across test-retest trials. Twenty-four resistance-trained males and females (age, 27.4 ± 4.0 y; body mass, 77.2 ± 12.6 kg; relative bench press one-repetition maximum [1-RM], 1.19 ± 0.23 kg•kg^{-1}) were assessed for their 1-RM in the free-weight bench press. After 48 to 72 hours, they were tested for the maximum number of achievable repetitions at 90%, 80% and 70% of their 1-RM. A retest was completed for all assessments one week later. Gathered data were used to model the relationship between relative load and repetitions to failure with respect to individual trends using Bayesian multilevel modeling and applying four recently proposed model types. The maximum number of repetitions showed slightly better reliability at lower relative loads (ICC at 70% 1-RM = 0.86, 90% highest density interval: [0.71, 0.93]) compared to higher relative loads (ICC at 90% 1-RM = 0.65 [0.39, 0.83]), whereas the absolute agreement was slightly better at higher loads (SEM at 90% 1-RM = 0.7 repetitions [0.5, 0.9]; SEM at 70% 1-RM = 1.1 repetitions [0.8, 1.4]). The linear regression model and the 2-parameters exponential regression model revealed the most robust parameter estimates across test-retest trials. Results testify to good reproducibility of repetition maximum tests at standardized relative loads obtained over short periods of time. A complementary free-to-use web application was developed to help practitioners calculate strength-endurance profiles and build individual repetition maximum tables based on robust statistical models.

INTRODUCTION

Dynamic strength endurance has previously been defined as the amount of concentric work an individual can produce in a cyclic or repetitive movement [1]. Assuming that the range of motion is approximately constant for each repetition of a given resistance training exercise, strength endurance can therefore be described by the number of repetitions performed to momentary failure (RTF) at a given load for a single sustained trial [1, 2]. The evaluation of strength endurance by means of a repetition maximum test (occasionally also called repetition endurance test) usually involves an exercise being performed to momentary failure at either a fixed absolute load, expressed in a unit of mass like kg or lbs, or a fixed relative load that has been normalized to the exercise-specific one-repetition maximum (1-RM). The concept is widely applied by coaches to guide resistance training programming [1, 3, 4]. However, given the fact that resistance training is usually carried out across a wider spectrum of loads, assessing the RTF an individual can execute at a single load only provides limited insight into a person's fatigue resistance. More meaningful insights into strength endurance could be obtained by studying the relationship between load and RTF (i.e., the individual "strength-endurance profile"). Additionally, knowledge of the mathematical relationship between the two variables could be used by practitioners to predict the load associated with a certain repetition maximum. This may be of particular interest for individuals seeking to control intensity of effort within a set [5] by prescribing a certain percentage of the maximum load that can be used for a given number of repetitions [6]. While other methods have been proposed to evaluate or control intensity of effort based on perceived effort or movement velocity [7], an approach using strength-endurance profiles might overcome certain limitations of these methods. Such limitations include inappropriate anchoring of perception [5], inaccurate subjective estimates of repetitions in reserve at lower intensity of effort [8] and dependency on technology to provide reliable feedback on movement velocity [9].

The relationship between load and RTF can be expressed through simple bivariate models. Thus far, research has proposed models that describe either a linear [10–12] or an exponential relationship [11–14]; usually, the respective model equations are then rearranged to predict the 1-RM from a repetition maximum test. However, studies conducted to test the validity of these equations often showed poor predictive accuracy, especially when the applied repetition maximum test was executed at loads allowing for 10 repetitions or more [3, 12, 13, 15–17]. The poor validity may be related to substantial inter-individual differences in strength-endurance relationships that models not incorporating the responsible confounding factors fail to account for. Indeed, there is evidence that the amount of repetitions that can be performed at a given relative load, and hence the strength-endurance relationship, may depend on various factors, such as qualitative and quantitative training background [11, 18–20], fiber type composition and the capillary density of involved muscles [21, 22], exercise [12, 19, 23] and movement cadence [14, 24]. A possible solution to overcome these challenges in modeling strength-endurance relationships has been proposed by Morton and colleagues [25] who introduced the idea of creating subject-specific models, thereby treating the individual person as the population of interest. For this purpose, the authors reformulated the critical power model originally proposed by Monod and Scherrer [26] such that it may be applied to isoinertial resistance training exercises. The resulting model has recently been referred to as critical load model and was originally presented as a non-linear function featuring three parameters [25, 27].

While the individualized modeling approach may reduce variance resulting from uncontrolled confounding variables, such models are typically estimated from a limited number of available data due to the exhaustive nature of sets performed to failure [25, 27]. Hence, the estimation of model parameters can be strongly affected by variability in test results, as single data points tend to have a larger influence on parameter estimates in small samples compared to large samples. Therefore, the robustness of individual strength-endurance models over short periods is crucial for their application in practice. The present study was designed to target two objectives: 1) to evaluate the consistency of the RTF at standardized relative loads and 2) to compare the reproducibility of four recently proposed models describing the individual strength-endurance relationship. A complementary, freely available web application will be provided to allow practitioners to easily calculate strength-endurance profiles based on a model that can be considered sufficiently robust to help with the design and regulation of resistance training programs.

MATERIALS AND METHODS

Subjects

Fifteen resistance-trained men (age = 27.2 ± 3.3 yrs, body mass = 85.4 ± 7.9 kg, bench press 1-RM/body mass = 1.33 ± 0.11 $kg \cdot kg^{-1}$) and nine resistance-trained women (age = 27.7 ± 5.2 y, body mass = 63.6 ± 3.3 kg, bench press 1-RM/body mass = 0.96 ± 0.17 $kg \cdot kg^{-1}$) volunteered to be tested for the present study. In order to participate, subjects had to be between 18 and 40 years of age, free of illness and injury and have at least one year of training experience in the bench press exercise as well as a 1-RM corresponding to at least 1x body mass for men and 0.75x body mass for women, respectively. Prior to physical testing, participants were informed about the possible risks, had to complete a modified physical activity readiness questionnaire (PAR-Q) and sign an informed consent form. The study was designed in fulfillment of the ethical guidelines communicated in the Declaration of Helsinki and approved by the host institution's local ethical committee (no. 00461).

Experimental approach

A test-retest design was used to determine the participants' maximum strength and strength-endurance at high loads in the free-weight bench press exercise on two occasions (T1 & T2) separated by one week (Figure 1). Maximum strength was assessed according to a progressive 1-RM test. Strength-endurance was assessed using repetition maximum tests at 90%, 80% and 70% of the 1-RM, respectively. In order to provide some rest, the 1-RM test and the repetition maximum tests were executed on two different days, separated by 48 to 72 hours, resulting in a total of four visits to the laboratory within 11 days. Importantly, the relative loads applied for the repetition maximum tests during the fourth visit were adjusted to the 1-RM achieved during the third visit. Consequently, a change in the 1-RM between T1 and T2 also implied a change in the absolute load used for the repetition maximum tests at T2, in order to ensure that trials were performed at 90%, 80% and 70% of the current 1-RM. All tests were completed at the same time of day.

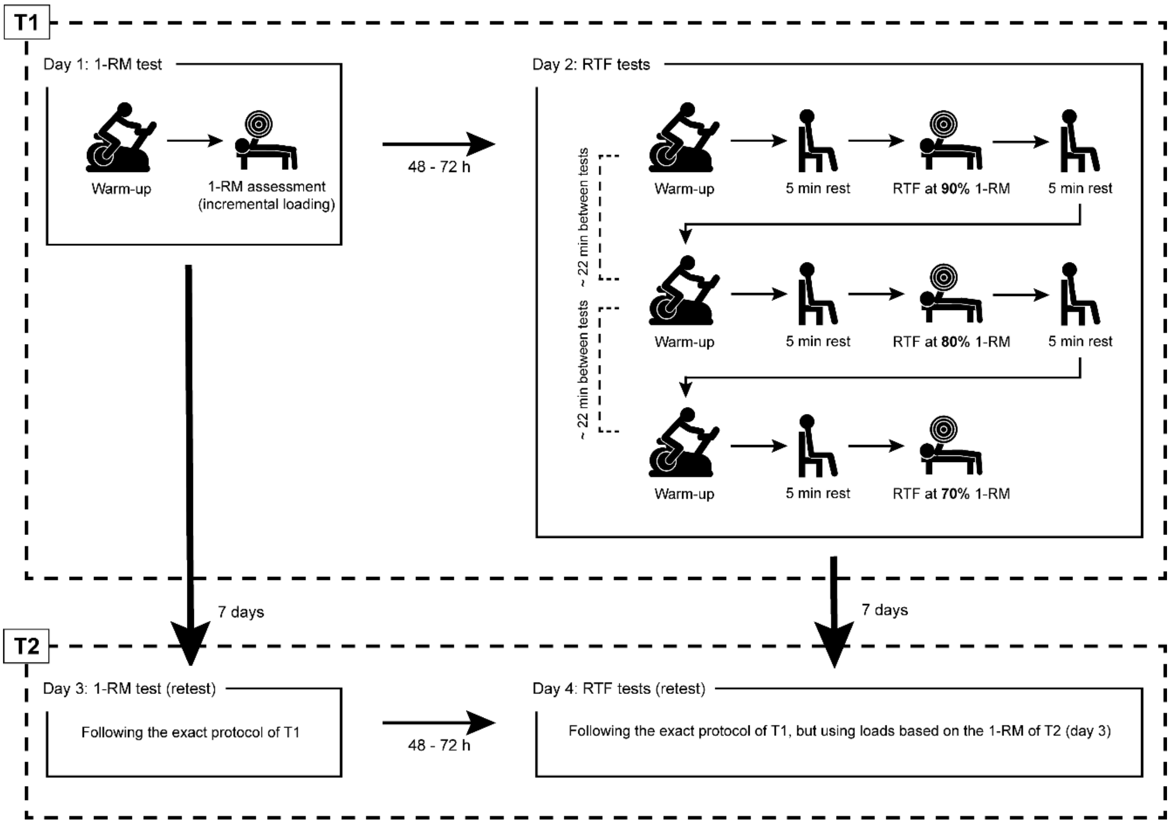

Fig 1. Experimental design. 1-RM, one-repetition maximum; RTF, repetitions performed to momentary failure.

Procedures

On the first day, subjects completed preliminary health screening and filled in a physical activity form to evaluate their experience with the tested exercise. Body height and body mass were assessed using a stadiometer (Seca Model 217; SECA GmbH & Co. KG., Hamburg, Germany) and scale (Seca Model 877; SECA GmbH & Co. KG., Hamburg, Germany). Participants then completed a standardized warm-up consisting of cycling for 5 min at a constant power output of 1 W per kg body mass and a rotational velocity of 80 rpm on an ergometer (Kettler X1, Trisport, Huenenberg, Switzerland), followed by a brief dynamic upper body mobilization routine. Subsequently, they were familiarized with the standardized movement technique for the bench press: each subject had to lower the barbell onto two safety pins, which were individually adjusted to a height that would allow for up to 3 cm of vertical distance between the bottom barbell position and the subject's chest. An experienced staff member visually ensured that the barbell was placed on the safety pins without rebound, before giving the verbal command "Press!", signaling the subject to execute the concentric phase of the bench press at maximum voluntary velocity. Participants were required to maintain their hip, shoulders and head positioned on the bench and their feet placed on the floor during each set.

Upon completion of the familiarization, participants were requested to estimate their 1-RM based on self-evaluation of their recent training performance. The subsequent 1-RM test featured a progressive loading pattern with the first five loads being fixed at 25%, 50%, 75%, 85% and 95% of the estimated 1-RM, while mean concentric barbell velocity was recorded with a linear position transducer (GymAware Power Tool, Kinetic Performance Technologies, Canberra, Australia). In the initial set, three repetitions were performed, followed by a 3-min break. Two repetitions were performed once the highest achieved velocity of the preceding set fell below 1.0 m/s, followed by a 4-min break and single repetitions were performed once it fell below 0.65 m/s, followed by a 5-min break. After successfully completing 95% of the estimated 1-RM, loads were increased individually to approximate the true 1-RM. The 1-RM was considered to be determined once a load increment of 2.5 kg from the preceding set would no longer allow the subject to complete the exercise across the full range of motion.

Repetition maximum tests were completed at 90%, 80% and 70% of the identified 1-RM, respectively, in the form of a single-visit protocol. Barbell loads were not randomized, but prescribed in a descending scheme, to minimize systematic effects of accumulated fatigue on the performance during subsequent sets [28]. In order to provide extended time for recovery in between repetition maximum tests, yet sustain warm-up effects during these periods, participants underwent the same general warm-up procedure that was used for the 1-RM test prior to each set to failure. Additionally, they performed a specific warm-up including three repetitions at 25%, three repetitions at 50% and two repetitions at 75% 1-RM prior to each set to failure. A passive rest of 3 min was provided between warm-up sets and additional 5 min before and immediately after each set to failure. Due to this methodological structure (i.e., the standardized warm-up; the standardized passive rest before and after each set to failure), the repetition maximum tests were separated by approximately 22 min each. Criteria for movement execution were kept identical to those communicated for the 1-RM test. Participants were instructed to lower the barbell in a controlled fashion on each repetition, albeit not being prescribed a fixed movement cadence. Similar to the 1-RM test, participants had to await the verbal command of the staff member before initiating the concentric phase of a repetition, in order to avoid any rebound from the safety pins. The concentric phase of each repetition had to be performed at maximum intended velocity. A repetition maximum test was terminated once the participant was unable to complete another repetition across the full range of motion despite using maximal effort, suggesting that the point of momentary failure had been reached [5].

Statistical Analysis

Reproducibility of performance measures

Statistics were calculated following a Bayesian approach using weakly informative priors. To assess test-retest reliability of the 1-RM and RTF at 90%, 80% and 70% 1-RM, respectively, the following random-intercept mixed effects model was used:

$$P_{ij} \sim Normal(\mu + s_i + \Delta t D_j, \sigma_e{}^2) \qquad [1]$$

In this model, P_{ij} describes the analyzed performance measure as a dependent variable, μ describes the mean performance for T1, s_i the random deviation from μ for subject *i*, Δt the fixed effect of time (i.e., the systematic difference in performance between T2 and T1), D_j a binary dummy variable for trial *j*, and σ_e^2 the variance of model residuals. The random effect parameter s_i was considered to be sampled from a normal distribution with a mean of 0 and a variance of σ_s^2, as suggested by Baumgartner and colleagues [29]. Posterior distributions for each model parameter were sampled using the Hamiltonian Monte Carlo algorithm of the probabilistic programming language Stan [30] controlled through an R interface (*rstan* R package, version 2.21.2). Based on the resulting random-intercept models, relative consistency (reliability) of each performance measure was evaluated using the Intraclass Correlation Coefficient (ICC), which was estimated and interpreted as the proportion of total variance ($\sigma_s^2 + \sigma_e^2$) attributed to the variance among subjects (σ_s^2) [29]. Furthermore, absolute consistency (agreement) of performance was quantified using the Standard Error of Measurement (SEM = σ_e), Within-Subject Coefficient of Variation (WSCV = SEM / μ) and Standard Error of Prediction (SEP = SD(1-ICC^2)$^{(1/2)}$) [29, 31, 32]. Posterior distributions of the statistics were summarized and interpreted according to the Maximum a Posteriori point estimate (MAP) and 90% Highest Density Interval (HDI) [33]. Effect directions supported by at least 90% of posterior probability were considered “clear” or “likely”.

Reproducibility of strength-endurance models

To describe the relationship between relative load and RTF with respect to individual trends, four previously proposed model types were expressed according to a multilevel (mixed effects) structure:

Lin: $load_i \sim Normal(\boldsymbol{a_i} + \boldsymbol{b_i} RTF_i, \sigma^2)$ [2]

Ex2: $load_i \sim Normal(\boldsymbol{a_i} e^{(\boldsymbol{b_i} RTF_i)}, \sigma^2)$ [3]

Ex3: $load_i \sim Normal(\boldsymbol{c_i} + \boldsymbol{a_i} e^{(\boldsymbol{b_i} RTF_i)}, \sigma^2)$ [4]

Crit: $load_i \sim Normal(\boldsymbol{L'_i} \,/\, (RTF_i - \boldsymbol{k_i}) + \boldsymbol{CL_i}, \sigma^2)$ [5]

Equation 2 (Lin) models the relationship as a linear regression. Equations 3 (Ex2) and 4 (Ex3) both describe exponential regression models, where Ex3 follows the structure of a commonly proposed 3-parameters model [11, 12, 14] and Ex2 constitutes a simplified 2-parameters version without the additive parameter $\boldsymbol{c_i}$ [13]. Equation 5 (Crit) presents the previously described critical load model adapted for relative load as dependent variable, using the original parameter labels ***L'***, ***k*** and ***CL*** [25, 27]. To evaluate how much parameter estimates for Equations 2 to 5 differ between T1 and T2, a change effect was added for each of the abovementioned subject-level parameters. For example, the parameter expression $\boldsymbol{a_i}$ was extended to ($\boldsymbol{a_i} + \Delta \boldsymbol{a_i} D_j$), where $\boldsymbol{a_i}$ reflects the target parameter at T1, $\Delta \boldsymbol{a_i}$ reflects the change effect (difference) of the target parameter between T2 and T1 and D_j reflects a binary dummy variable for trial *j*. Importantly, all of the abovementioned parameters were modeled as random effects that were free to vary across subjects. The multilevel structure was realized by sampling subject-level parameters and change effects from multivariate normal distributions, applying covariance matrices to account for possible correlations among subject-level parameters and change effects, respectively. Further details on models and prior selection are provided online (Supporting information 1).

A posterior predictive distribution was calculated by drawing random samples from the respective group-level (fixed effects) distribution of each change effect and the draws were standardized to the scale of the associated model parameter at T1. The resulting posterior predictive distributions were summarized and compared to a threshold for acceptable differences that was set at ±0.6, reflecting a small or trivial standardized change of the parameter [34]. Change effects were also expressed as a percentage of the group-level mean of the associated model parameter at T1 to facilitate the interpretation of parameters that are exceptionally homogeneous across subjects.

RESULTS

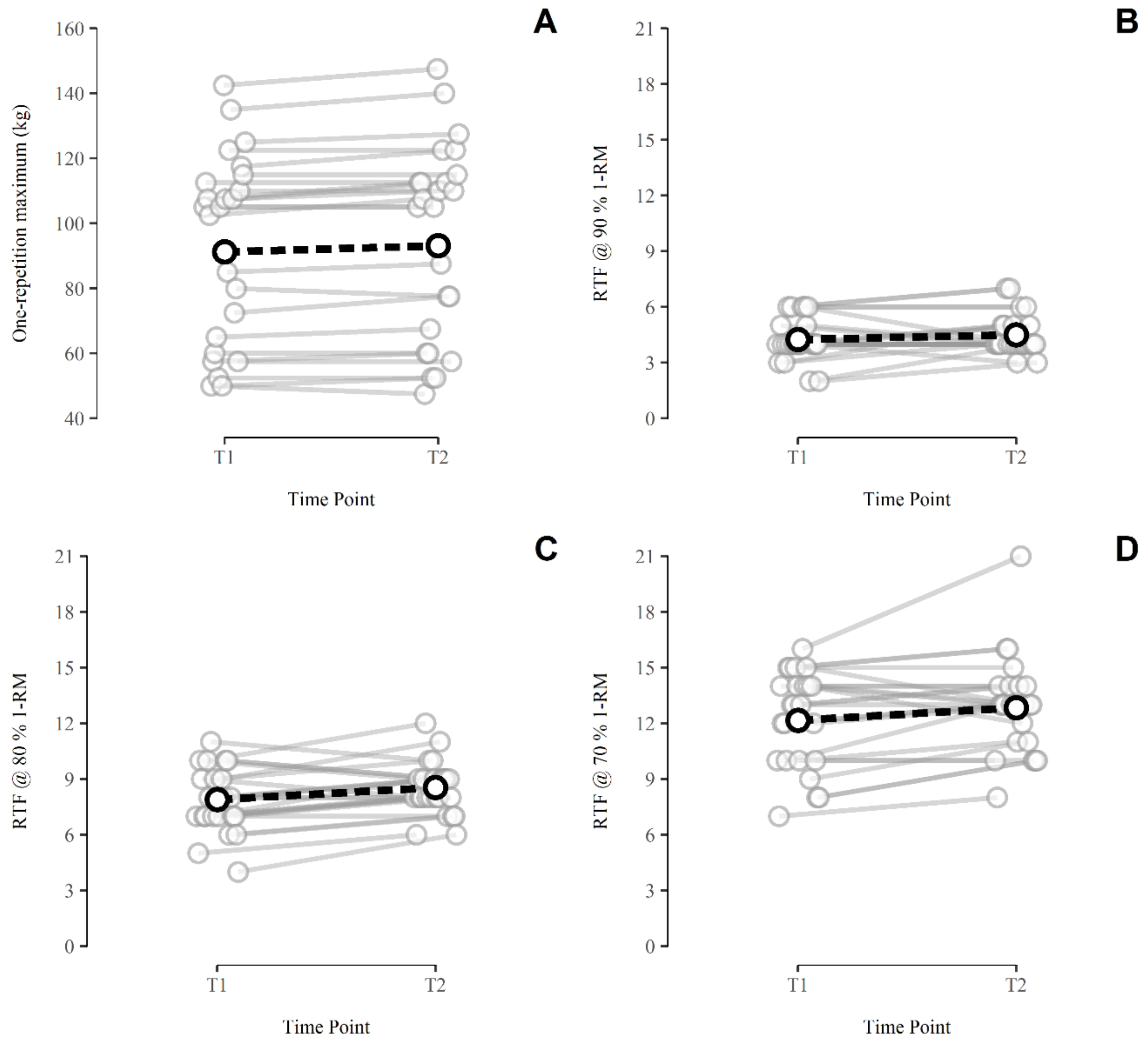

Fig 2. Variability of strength performance in the bench press. A, one-repetition maximum (1-RM); B, repetitions performed to momentary failure (RTF) at 90% 1-RM; C, RTF at 80% 1-RM; D, RTF at 70% 1-RM; grey circles, data points (jittered illustration); black circles, group means; solid grey lines, individual performance changes; dashed black lines, systematic performance changes (Δt).

The variability of 1-RM performance as well as the RTF performed at 90%, 80% and 70% 1-RM is shown in Figure 2. On average, there was an increase in performance between T1 and T2 (Δt), the 90% HDI suggesting a small systematic increase of the 1-RM, the RTF at 80% 1-RM and the RTF at 70% 1-RM. Regarding relative consistency of performance, the 1-RM yielded nearly perfect reliability, with the ICC being close to 1. The RTF, on the other hand, showed a trend for higher relative consistency at lower loads, although the difference between load conditions was not statistically clear at the 90% credibility level. Analysis of absolute consistency revealed the SEM for the 1-RM to be likely less than 2.2 kg (90th percentile). Concerning the RTF performed at submaximal loads, the SEM was likely less than 1 repetition at 90% and 80% 1-RM, and likely less than 1.5 repetitions at 70% 1-RM. Subject performance and consistency statistics are summarized in Table 1.

Posterior predictive distributions of subject-level model parameters at T1 and T2 are summarized in Table 2. Moreover, posterior predictive distributions for standardized change effects are shown in Figure 3. The critical load model revealed a systematic positive change effect for ***L'*** [p ($\boldsymbol{\Delta L'_i}$ > 0 | data) > 99.9%] and systematic negative change effects for ***k*** [p ($\boldsymbol{\Delta k_i}$ < 0 | data) > 99.9%] and ***CL*** [p ($\boldsymbol{\Delta CL_i}$ < 0 | data) = 97.3%]. Similarly, the 3-parameters exponential model showed a systematic positive change effect for ***c*** [p ($\boldsymbol{\Delta c_i}$ > 0 | data) = 99.7%] and systematic negative change effects for ***a*** [p ($\boldsymbol{\Delta a_i}$ < 0 | data) = 99.6%] and ***b*** [p ($\boldsymbol{\Delta b_i}$ < 0 | data) = 96.4%]. None of the remaining models' parameters resulted in a clear positive or negative change at the 90% credibility level. No model parameter resulted in a clearly small or trivial change at the chosen credibility level and threshold for acceptable differences. However, the slope parameter of the linear model (***b***) and the curvature parameter of the 2-parameters exponential model (***b***) indicated a probability of >80% for the change effect to be small or trivial. Furthermore, both intercept parameters (***a***) of the linear model and the 2-parameters exponential model indicated relative change effects close to 0 (Table 3).

Table 1. Consistency statistics for strength performance in the bench press.

	1-RM (kg)	RTF at 90% 1-RM (n)	RTF at 80% 1-RM (n)	RTF at 70% 1-RM (n)
Performance				
T1	93.5 ± 28.9	4.2 ± 1.2	7.8 ± 1.7	12.2 ± 2.6
T2	95.4 ± 29.9	4.5 ± 1.1	8.5 ± 1.4	12.9 ± 2.6
Δt	1.9 [1.0, 2.7]	0.2 [-0.1, 0.6]	0.7 [0.3, 1.0]	0.7 [0.2, 1.2]
Absolute consistency				
SEM	1.7 [1.4, 2.3]	0.7 [0.5, 0.9]	0.7 [0.6, 1.4]	1.1 [0.8, 1.4]
WSCV (%)	1.8 [1.4, 2.5]	15.9 [12.3, 21.3]	9.2 [7.2, 12.2]	8.8 [6.9, 11.8]
SEP	2.3 [1.6, 3.3]	0.9 [0.7, 1.1]	0.9 [0.7, 1.9]	1.4 [1.0, 1.9]
Relative consistency				
ICC	1.00 [0.99, 1.00]	0.65 [0.39, 0.83]	0.82 [0.64, 0.93]	0.86 [0.71, 0.93]

Sample data are presented as mean ± standard deviation.

Statistics are presented as Maximum a Posteriori estimate [90% Highest Density Interval].

1-RM, one-repetition maximum; Δt, fixed effect of time; ICC, interclass correlation coefficient; RTF, repetitions performed to momentary failure; SEM, standard error of measurement; SEP, standard error of prediction; T1, baseline test; T2, retest; WSCV, within-subject coefficient of variation.

Table 2. Summary of posterior predictive distributions of absolute parameter values during test (T1) and retest (T2).

Model	Parameter	T1	T2	Δx_i (T2 – T1)
Lin	a	101.5 [100.3, 102.5]	101.9 [100.4, 103.4]	0.4 [-0.8, 1.6]
	b	-2.73 [-3.77, -1.68]	-2.56 [-3.64, -1.47]	0.09 [-0.23, 0.47]
Ex2	a	102.6 [101.6, 103.8]	102.9 [101.5, 104.4]	0.3 [-0.9, 1.5]
	b	-0.031 [-0.044, -0.020]	-0.030 [-0.043, -0.017]	0.002 [-0.002, 0.006]
Ex3	a	76.3 [65.1, 95.3]	63.4 [55.0, 75.2]	-12.7 [-25.1, -4.5]
	b	-0.045 [-0.068, -0.022]	-0.054 [-0.080, -0.032]	-0.010 [-0.021, -0.001]
	c	27.3 [7.2, 38.1]	40.7 [27.9, 48.8]	13.7 [5.2, 25.9]
Crit	L’	3638.8 [2062.5, 6422.1]	4583.0 [2637.9, 7271.6]	613.7 [287.6, 1129.9]
	k	-32.0 [-47.5, -20.5]	-36.5 [-52.0, -24.3]	-4.1 [-6.6, -2.0]
	CL	-17.4 [-43.4, 3.6]	-23.5 [-48.5, -2.5]	-3.3 [-8.8, 0.0]

Posterior predictive distributions are summarized using the Maximum a Posteriori estimate and 90% Highest Density Interval.

Crit, critical load model; Ex2, exponential model (2 parameters); Ex3, exponential model (3 parameters); Lin, linear model; Δx_i, change effect between T1 and T2.

Table 3. Summary of posterior predictive distributions of relative and standardized change effects.

Model	Change effect	Relative magnitude (%) *	Standardized magnitude **	p ($\Delta x_i \in$ [-0.6, 0.6] | data) **
Lin	Δa	0.3 [-0.8, 1.6]	0.38 [-4.46, 8.98]	27.6%
	Δb	4.8 [-8.9, 17.2]	0.17 [-0.38, 0.78]	86.9%
Ex2	Δa	0.4 [-1, 1.4]	0.13 [-4.43, 9.35]	29.5%
	Δb	4.6 [-7.9, 18.1]	0.22 [-0.36, 0.8]	84.8%
Ex3	Δa	-19.1 [-28.5, -7.8]	-15.26 [-184.85, 0.71]	0.2%
	Δb	-20.4 [-48.5, -0.7]	-0.83 [-2, -0.04]	26.1%
	Δc	42.1 [0.4, 217.4]	18.34 [0.05, 232.88]	0.1%
Crit	ΔL’	14.6 [6.7, 29.6]	0.76 [0.24, 1.83]	18.8%
	Δk	-12.1 [-22.1, -6]	-0.63 [-1.26, -0.24]	36.2%
	ΔCL	-10.9 [-129.6, 7.8]	-1.2 [-6.4, 0.52]	11.5%

Posterior predictive distributions are summarized using the Maximum a Posteriori estimate and 90% Highest Density Interval.

*, change effects are expressed relative to the group-level mean of the associated model parameter at T1.

**, change effects are standardized to the group-level standard deviation of the associated model parameter at T1. Crit, critical load model; Ex2, exponential model (2 parameters); Ex3, exponential model (3 parameters); Lin, linear model; p ($\Delta x_i \in$ [-0.6, 0.6] | data), probability of the standardized change effect falling within the threshold for acceptable differences given the data.

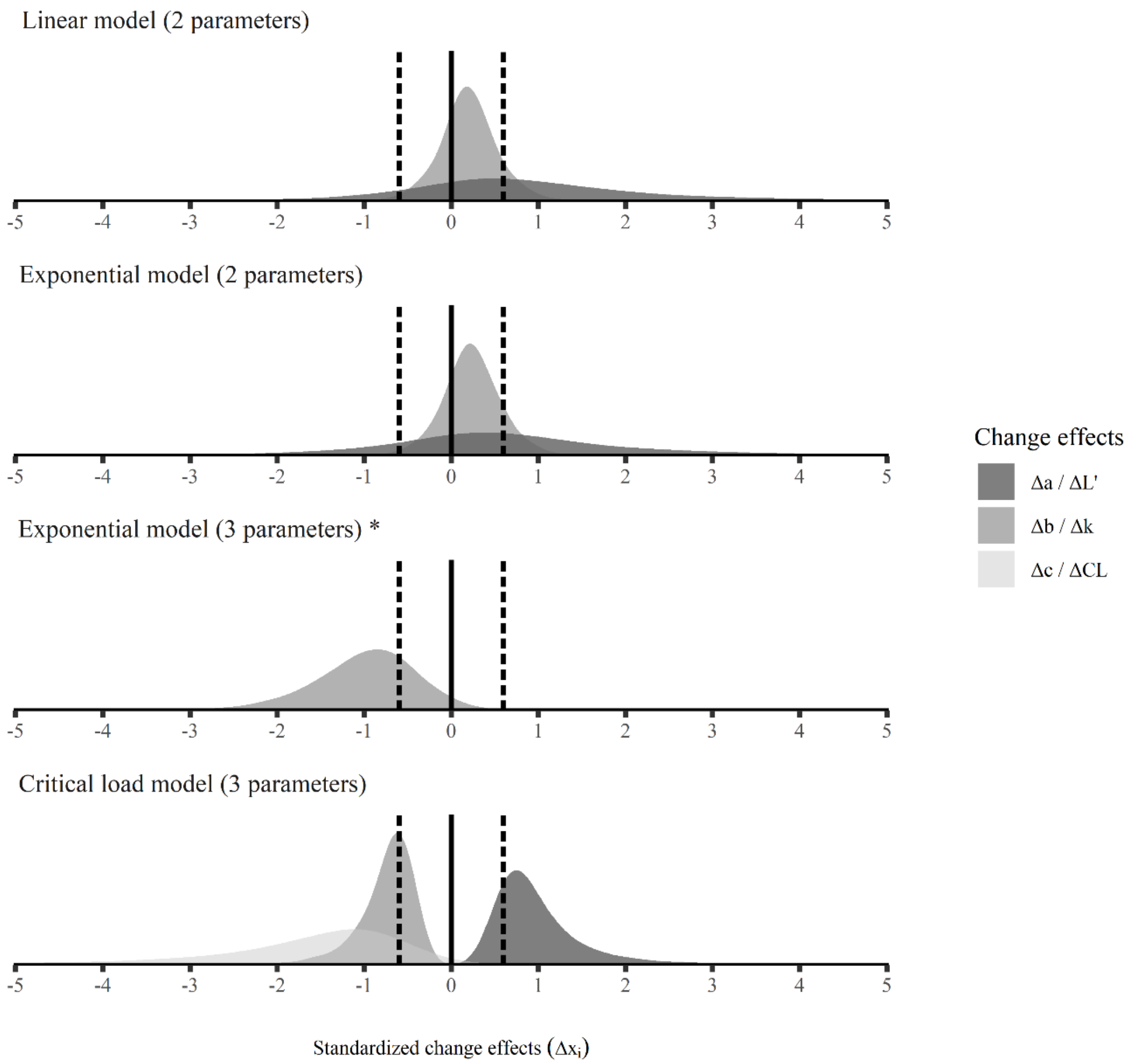

Fig 3. Posterior predictive distributions for standardized subject-level change effects (smoothed illustration). Dashed black lines, threshold for acceptable differences set to [-0.6, 0.6] indicating small or trivial changes; *, change effects ***Δa*** and ***Δc*** of the exponential 3-parameters model are not visibly displayed due to very large scales.

DISCUSSION

The present study was designed to address two objectives: first, we evaluated the reliability and agreement of RTF performed at 90, 80 and 70% 1-RM in the bench press exercise. Second, we aimed to analyze the reproducibility of four different models representing the individual strength-endurance relationship to identify which ones provide the most robust parameter estimates. Test-retest analysis of performance indicated very good reproducibility of the 1-RM and the RTF at high relative loads in the bench press exercise. The linear regression and the 2-parameters exponential regression yielded the most robust parameter estimates across the investigated models of the strength-endurance relationship.

The 1-RM revealed both very high relative and absolute consistency. In particular, the SEM for the 1-RM was found to be likely less than the smallest load increment applied during the 1-RM assessment in the present study (2.5 kg). These findings correspond to previous research reporting excellent reliability of 1-RM performance in the bench press exercise [4, 35, 36]. Similarly, the RTF at 90, 80 and 70% 1-RM revealed high absolute consistency, the SEM likely being less than 1.5 repetitions at 70% 1-RM, and less than 1 repetition at 90% and 80% 1-RM. Posterior distribution analysis revealed no systematic differences of SEM between RTF performed at 70%, 80% and 90% 1-RM. However, a slight shift of SEM posterior distributions to lower values could be observed for RTF at higher relative loads. In particular, the difference of SEM between RTF at 70% and 90% 1-RM could have exceeded the predefined threshold for systematic differences at a larger sample size. Interestingly, the ICC showed an opposing non-systematic shift of posterior distributions, with lower relative loads resulting in slightly larger ICC values. These seemingly contradictory trends arising from absolute and relative consistency might be related to the computation of the respective statistics: in the present study, the ICC was calculated as the proportion of total variance attributed to the variance among subjects. Therefore, it tends to be smaller when between-subject variance is low and SEM is large. Indeed, our data suggest a higher between-subject variance of the RTF at 70% 1-RM compared to 90% 1-RM. A similar trend for heteroscedasticity in the relationship between relative load and RTF across individuals (i.e. a mean-variance “tradeoff”) has been reported on numerous occasions [3, 11, 12, 14, 18, 19, 37, 38]. This phenomenon could be the result of normalizing the load to the 1-RM, which homogenizes the upper end of the load spectrum. However, it could also be partially explained by inter-individual differences in the strength-endurance relationship.

Conforming trends for the reliability of the RTF performed at given relative loads can be observed from other sources. For example, Anders and colleagues reported an ICC of 0.90 (95% CI: [0.58, 0.97]) for RTF completed at 70% 1-RM in the bench press [4], indicating a similar magnitude compared to the present study (ICC [90% HDI] = 0.86 [0.71, 0.93]). While the reported SEM of 0.68 repetitions was noticeably lower compared to the present study, the authors also described a lower between-subject standard deviation of ±1.5 repetitions. Similarly, Pereira and colleagues reported an ICC of 0.90 for the RTF achieved at 75% 1-RM in the bench press, when performing repetitions at a joint velocity of 100°/s. While no information on subject heterogeneity was provided, the authors also reported an ICC of 0.70 when the exercise was completed at a joint velocity of 25°/s. It could be hypothesized that the reduced movement cadence might have negatively affected the number of repetitions performed [14, 24], possibly due to an increased duration of the concentric phase of each repetition and associated increases in metabolic demand [39]. Hence, a reduced movement cadence at lower loads could result in a distribution of RTF that is similar to the RTF at higher loads when repetitions are performed at maximal voluntary velocity, as was the case in the present study.

Other studies investigated the reproducibility of RTF in absolute loads. For example, Mann et al. analyzed the test-retest reliability of NCAA Division I football players in the NFL-225 test, which is a repetition maximum test using a fixed load of 225 lbs or 102.3 kg in the bench press exercise [40]. The authors reported an ICC of 0.98 to 0.99 and a typical error of 1.0 to 1.3 repetitions across three trials, the typical error corresponding to what has been calculated as SEM in the present study. While it is difficult to evaluate at what percentage of the 1-RM each participant performed the NFL-225 test in the absence of a 1-RM test, the authors estimated it to be around 67.9% 1-RM for athletes with a body mass below 100.5 kg and around 44.6% 1-RM for heavier athletes. Therefore, the majority of participants performed the NFL-225 test at lower relative loads compared to the present study. Given this fact, the reports of Mann et al. [40] correspond well to the results of the present study (SEM for RTF at 70% 1-RM [90% HDI] = 1.1 [0.8, 1.4] repetitions), especially when considering the large between-subject variance reported by the authors, which may have contributed to the large ICC, as discussed before. Finally, Rose and Ball analyzed the reliability of the RTF that could be achieved against 15.9 kg and 20.4 kg, reporting an ICC of 0.97 in both cases [36]. In their sample of 21 moderately trained women the two tested loads corresponded roughly to a mean relative load of 42% and 54% 1-RM, which supports the hypothesis of RTF tests showing higher relative consistency at low loads.

A systematic increase in the 1-RM between test and retest has previously been described on numerous occasions for various exercises [41]. Interestingly, Ribeiro and colleagues reported that this time effect did not interact significantly with participants' experience in resistance training [42]. While the magnitude of the systematic change (Δt [90% HDI] = 1.9 kg [1.0, 2.7]) could be considered trivial in the present study, given the smallest load increment was 2.5 kg, previous research suggested that the effect may occur over the course of multiple consecutive retest trials as a result of practicing the test [42–44]. Similarly, the time effect of RTF performed at 90%, 80% and 70%-1RM showed a high probability for being less than 1 repetition. Despite the RTF at 80% and 70% 1-RM indicating a systematic difference between T1 and T2, the magnitude of this effect is likely trivial.

To the best of our knowledge, this is the first study to evaluate and compare the reproducibility of different strength-endurance models with respect to individual trends. Not all of the investigated models resulted in robust parameter estimates over time. Most notably, the 3-parameters exponential model and the critical load model exhibited systematic changes for all parameters. These findings suggest that naturally occurring variability in strength performance likely causes parameter estimates to systematically change, even over short periods, and that the magnitude of these changes is unacceptably high in relation to the respective parameter's group-level standard deviation. Therefore, the two models may not provide sufficient reproducibility for application in the practical field. In comparison, the linear model and the 2-parameters exponential model both resulted in a high probability for ***Δb*** (i.e., the change in slope and curvature parameters, respectively) to fall within the threshold for acceptable differences, although the effects were not clear at the selected credibility level. No clear change effect could be identified for the intercept parameter ***a*** in both cases due to low between-subject variability. However, findings suggest a negligible relative magnitude for ***Δa*** in both models (Table 3). Therefore, both the linear model and 2-parameters exponential model yield the most robust parameter estimates across test-retest trials among the investigated models. To decide which of the two models to apply in a practical setting, practitioners should also consider statistical qualities other than the robustness of models. For example, both the model fit und predictive validity can be considered essential characteristics of a valuable strength-endurance profile. While previous research provided some evidence that the relationship may be considered approximately linear at high loads [3, 10–12], it has been suggested that the relationship actually follows a curvilinear trend when considering the full spectrum of loads [11, 13, 14]. Therefore, practitioners might want to resort to applying the 2-parameters exponential regression rather than the linear regression to model strength-endurance profiles, as research has not proposed any explicit disadvantages reasoning against its use.

Based on the findings of the present study, a freely available web application was developed using the R package *shiny* (version 1.7.1). The application provides practitioners with a user-friendly interface to enter data from repetition maximum tests and offers different algorithms to compute the individual and exercise-specific strength-endurance profile. Upon computation, it offers a graphical display of the profile, a model equation and an adjusted R^2 estimate to evaluate model fit. Furthermore, it produces an individual repetition-maximum table based on the estimated model parameters that predicts loads for a wider spectrum of RTF. A link to the web application is provided at the end of this article.

It should be pointed out that the order of repetition maximum tests was not randomized in the present study. Hence, a possible systematic effect of the earlier sets performed to momentary failure on subsequent sets and, thus, the presence of systematic bias in the RTF performed cannot be excluded. Future research should strive to compare different test protocols and identify a valid, yet practically applicable approach to acquiring the necessary data for model computation. However, the results of the present study may help practitioners understand the consistency of strength performance under standardized conditions and can assist with the selection of a reliable statistical model to calculate individual strength-endurance profiles.

CONCLUSIONS AND PRACTICAL APPLICATIONS

In conclusion, both the 1-RM and RTF at 90%, 80% and 70% 1-RM showed good reproducibility over test-retest trials in the bench press exercise for trained subjects. When modeling the relationship between load and RTF using a multilevel structure, the linear regression and 2-parameters exponential regression provide more stable parameter estimates than the 3-parameters exponential regression or critical load model.

To calculate a strength-endurance profile for a given individual and specific exercise, it is recommended to acquire the maximum number of repetitions that can be performed to momentary failure against three different loads. While the loads should be chosen according to a range of interest, practitioners should expect to experience higher absolute day-to-day variability of RTF at lower loads. For loads in the range of 70% - 100% 1-RM, a linear regression or a 2-parameters exponential regression should be applied to reliably model the relationship between tested loads and the number of achieved repetitions. To derive a robust strength-endurance profile, practitioners can access a free-to-use web application using the following link:

https://strength-and-conditioning-toolbox.shinyapps.io/Strength-Endurance_Profile/

ACKNOWLEDGMENTS

The authors would like to thank all participants for contributing to the realization of the present study. The authors further want to express their gratitude to the Centre for Sport Science and University Sports, University of Vienna for providing the equipment and facilities.

REFERENCES

1. Lawton TW, Cronin JB, McGuigan MR. Strength testing and training of rowers: a review. Sports Med 2011; 41(5):413–32.
2. American College of Sports Medicine. American College of Sports Medicine position stand. Progression models in resistance training for healthy adults. Med Sci Sports Exerc 2009; 41(3):687–708.

3. Brechue WF, Mayhew JL. Upper-body work capacity and 1RM prediction are unaltered by increasing muscular strength in college football players. J Strength Cond Res 2009; 23(9):2477–86.
4. Anders JPV, Keller JL, Smith CM, Hill EC, Housh TJ, Schmidt RJ et al. The Effects of Asparagus Racemosus Supplementation Plus 8 Weeks of Resistance Training on Muscular Strength and Endurance. J Funct Morphol Kinesiol 2020; 5(1):4.
5. Steele J, Fisher J, Giessing J, Gentil P. Clarity in reporting terminology and definitions of set endpoints in resistance training. Muscle Nerve 2017; 56(3):368–74.
6. DeWeese BH, Hornsby G, Stone M, Stone MH. The training process: Planning for strength–power training in track and field. Part 2: Practical and applied aspects. J Sport Health Sci 2015; 4(4):318–24.
7. Suchomel TJ, Nimphius S, Bellon CR, Hornsby WG, Stone MH. Training for Muscular Strength: Methods for Monitoring and Adjusting Training Intensity. Sports Med 2021; 51(10):2051–66.
8. Hackett DA, Cobley SP, Davies TB, Michael SW, Halaki M. Accuracy in Estimating Repetitions to Failure During Resistance Exercise. J Strength Cond Res 2017; 31(8):2162–8.
9. García-Ramos A, Torrejón A, Feriche B, Morales-Artacho AJ, Pérez-Castilla A, Padial P et al. Prediction of the Maximum Number of Repetitions and Repetitions in Reserve From Barbell Velocity. Int J Sports Physiol Perform 2018; 13(3):353–9.
10. Brzycki M. Strength Testing - Predicting a One-Rep Max from Reps-to-Fatigue. JOPERD 1993; 64(1):88–90.
11. Desgorces FD, Berthelot G, Dietrich G, Testa MSA. Local muscular endurance and prediction of 1 repetition maximum for bench in 4 athletic populations. J Strength Cond Res 2010; 24(2):394–400.
12. Reynolds JM, Gordon TJ, Robergs RA. Prediction of One Repetition Maximum Strength from Multiple Repetition Maximum Testing and Anthropometry. J Strength Cond Res 2006; 20(3):584–92.
13. Mayhew JL, Johnson BD, Lamonte MJ, Lauber D, Kemmler W. Accuracy of prediction equations for determining one repetition maximum bench press in women before and after resistance training. J Strength Cond Res 2008; 22(5):1570–7.
14. Sakamoto A, Sinclair PJ. Effect of movement velocity on the relationship between training load and the number of repetitions of bench press. J Strength Cond Res 2006; 20(3):523–7.
15. LeSuer DA, McCormick JH, Mayhew JL, Wasserstein RL, Arnold MD. The Accuracy of Prediction Equations for Estimating 1-RM Performance in the Bench Press, Squat, and Deadlift. J Strength Cond Res 1997; 11(4):211–3.

16. Ware JS, Clemens CT, Mayhew JL, Johnston TJ. Muscular endurance repetitions to predict bench press and squat strength in college football players. J Strength Cond Res 1995; 9(2):99–103.
17. Wood TM, Maddalozzo GF, Harter RA. Accuracy of Seven Equations for Predicting 1-RM Performance of Apparently Healthy, Sedentary Older Adults. Meas Phys Educ Exerc Sci 2002; 6(2):67–94.
18. Richens B, Cleather DJ. The relationship between the number of repetitions performed at given intensities is different in endurance and strength trained athletes. Biol Sport 2014; 31(2):157–61.
19. Hoeger WW, Hopkins DR, Barette SL, Hale DF. Relationship between repetitions and selected percentages of one repetition maximum: A comparison between un-trained and trained males and females. J Strength Cond Res 1990; 4(2):47–54.
20. Pick J, Becque MD. The Relationship Between Training Status and Intensity on Muscle Activation and Relative Submaximal Lifting Capacity During the Back Squat. J Strength Cond Res 2000; 14(2):175–81.
21. Douris PC, White BP, Cullen RR, Keltz WE, Meli J, Mondiello DM et al. The relationship between maximal repetition performance and muscle fiber type as estimated by non-invasive technique in the quadriceps of untrained women. J Strength Cond Res 2006; 20(3):699–703.
22. Terzis G, Spengos K, Manta P, Sarris N, Georgiadis G. Fiber type composition and capillary density in relation to submaximal number of repetitions in resistance exercise. J Strength Cond Res 2008; 22(3):845–50.
23. Shimano T, Kraemer WJ, Spiering BA, Volek JS, Hatfield DL, Silvestre R et al. Relationship between the number of repetitions and selected percentages of one repetition maximum in free weight exercises in trained and untrained men. J Strength Cond Res 2006; 20(4):819–23.
24. LaChance PF, Hortobagyi T. Influence of Cadence on Muscular Performance During Push-up and Pull-up Exercise. J Strength Cond Res 1994; 8(2):76–9.
25. Morton RH, Redstone MD, Laing DJ. The Critical Power Concept and Bench Press: Modeling 1RM and Repetitions to Failure. Int J Exerc Sci 2014; 7(2):152–60.
26. Monod H, Scherrer J. The Work Capacity of a Synergic Muscular Group. Ergonomics 1965; 8(3):329–38.
27. Bergstrom HC, Dinyer TK, Succi PJ, Voskuil CC, Housh TJ. Applications of the Critical Power Model to Dynamic Constant External Resistance Exercise: A Brief Review of the Critical Load Test. Sports (Basel) 2021; 9(2):15.
28. Sánchez-Medina L, González-Badillo JJ. Velocity loss as an indicator of neuromuscular fatigue during resistance training. Med Sci Sports Exerc 2011; 43(9):1725–34.

29. Baumgartner R, Joshi A, Feng D, Zanderigo F, Ogden RT. Statistical evaluation of test-retest studies in PET brain imaging. EJNMMI Res 2018; 8(1):13.
30. Carpenter B, Gelman A, Hoffman MD, Lee D, Goodrich B, Betancourt M et al. Stan : A Probabilistic Programming Language. J. Stat. Soft. 2017; 76(1):32.
31. Vet HCW de, Terwee CB, Knol DL, Bouter LM. When to use agreement versus reliability measures. J Clin Epidemiol 2006; 59(10):1033–9.
32. Weir JP. Quantifying test-retest reliability using the intraclass correlation coefficient and the SEM. J Strength Cond Res 2005; 19(1):231–40.
33. Makowski D, Ben-Shachar M, Lüdecke D. bayestestR: Describing Effects and their Uncertainty, Existence and Significance within the Bayesian Framework. JOSS 2019; 4(40):1541.
34. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. Med Sci Sports Exerc 2009; 41(1):3–13.
35. Pereira MIR, Gomes PSC. Muscular strength and endurance tests: reliability and prediction of one repetition maximum – Review and new evidences. Rev Bras Med Esporte 2003; 9(5):336–46.
36. Rose K, Ball TE. A Field Test for Predicting Maximum Bench Press Lift of College Women. J Strength Cond Res 1992; 6(2):103–6.
37. Moss AC, Dinyer TK, Abel MG, Bergstrom HC. Methodological Considerations for the Determination of the Critical Load for the Deadlift. J Strength Cond Res 2021; 35(Suppl 1):S31-S37.
38. Dinyer TK, Byrd MT, Vesotsky AN, Succi PJ, Bergstrom HC. Applying the Critical Power Model to a Full-Body Resistance-Training Movement. Int J Sports Physiol Perform 2019; 14(10):1364–70.
39. Fountain WA, Valenti ZJ, Lynch CE, Guarnera SR, Meister BM, Carlini NA et al. Order of concentric and eccentric muscle actions affects metabolic responses. J Sports Med Phys Fitness 2021; 61(12):1587–95.
40. Mann JB, Ivey PJ, Brechue WF, Mayhew JL. Reliability and smallest worthwhile difference of the NFL-225 test in NCAA Division I football players. J Strength Cond Res 2014; 28(5):1427–32.
41. Grgic J, Lazinica B, Schoenfeld BJ, Pedisic Z. Test-Retest Reliability of the One-Repetition Maximum (1RM) Strength Assessment: a Systematic Review. Sports Med Open 2020; 6(1):31.
42. Ribeiro AS, do Nascimento MA, Mayhew JL, Ritti-Dias RM, Avelar A, Okano AH et al. Reliability of 1RM test in detrained men with previous resistance training experience. IES 2014; 22(2):137–43.

43. Mattocks KT, Buckner SL, Jessee MB, Dankel SJ, Mouser JG, Loenneke JP. Practicing the Test Produces Strength Equivalent to Higher Volume Training. Med Sci Sports Exerc 2017; 49(9):1945–54.
44. Dankel SJ, Counts BR, Barnett BE, Buckner SL, Abe T, Loenneke JP. Muscle adaptations following 21 consecutive days of strength test familiarization compared with traditional training. Muscle Nerve 2017; 56(2):307–14.

SUPPORTING INFORMATION

S1 Appendix. Modeling details.

This file contains detailed information on priors and models.

https://doi.org/10.1371/journal.pone.0268074.s001

(PDF)

S2 Table. Raw Data.

This file contains the data used for the statistical analyses.

https://doi.org/10.1371/journal.pone.0268074.s002

(XLSX)

2.3 Publication 3: Data Collection for Strength-Endurance Profiles: Can Assessments Be Completed within a Single Session?

Authors:

Benedikt Mitter, Peter Raidl, Robert Csapo, Pascal Bauer and Harald Tschan

Publication status:

The article was submitted to the Journal of Sports Sciences on October 24th, 2022.

Authors' contribution:

Benedikt Mitter: methodological conceptualization, project administration, data acquisition, data curation, data analysis, visualization, app conceptualization & development, writing of the original draft

Peter Raidl: project administration, data acquisition, writing of the original draft, proof-reading

Robert Csapo: project administration, writing of the original draft, proof-reading

Pascal Bauer: visualization, writing of the original draft, proof-reading

Harald Tschan: project supervision, methodological conceptualization, project administration, writing of the original draft, proof-reading

All authors listed above contributed to the present manuscript and approved the final version of it.

ABSTRACT

The objectives of this study were A) to compare two different protocols for the assessment of strength-endurance at multiple loads and B) to identify an appropriate model function for the relationship between load and the number of repetitions performed to momentary failure (RTF). Fourteen resistance-trained men underwent a one-repetition maximum (1-RM) test in the bench press exercise. In the following four sessions, they were tested for the RTF at 90%, 80%, and 70% 1-RM: once in the form of a single-visit protocol (SV, all loads being tested in the same session) and once in the form of a multi-visit protocol (MV, only one load being tested per session). While both protocols resulted in an equivalent number of repetitions at 90% 1-RM (mean difference [95% Highest Density Interval]: 0.0 repetitions [-0.6, 0.7]), the difference was statistically inconclusive at 80% 1-RM (0.4 repetitions [-0.3, 1.2]). Importantly, the MV protocol allowed for a larger number of repetitions to be performed at 70% 1-RM (1.9 repetitions [0.9, 2.7]). Analysis of model functions, when conducted with the data collected from the MV protocol, revealed that the relationship between load and RTF tends to be represented best by the reciprocal model and the 2-parameters exponential model.

KEY WORDS

Resistance training, local muscular endurance, repetitions to failure, modeling, single-visit, multi-visit

KEY POINTS

- When completing multiple RTF tests in a single session using a declining order of loads and separating tests by 22 min (SV protocol), the number of repetitions achieved is likely progressively biased in subsequent tests.
- For the touch-and-go bench press exercise, the relationship between load and RTF follows a curvilinear trend at loads ranging from 70% to 100% 1-RM.
- When distributing RTF tests across multiple sessions (MV protocol), strength-endurance profiles of the touch-and-go bench press exercise should be modeled using either the 2-parameters exponential regression or reciprocal regression.

INTRODUCTION

Prescribing training loads as a percentage of the individual one-repetition maximum (1-RM) is a well-established practice in resistance training programming and frequently applied in experimental research to standardize training loads across participants (Hickmott et al., 2022; Suchomel et al., 2021). Once the desired training load is fixed, the number of repetitions performed in a given set affects the degree of effort, as determined by the proximity to momentary failure at the set endpoint (Steele et al., 2017). Various methods have been proposed to evaluate and approximately control the degree of effort at a submaximal level, including autoregulative methods that apply either subjective perception of effort (e.g., repetitions in reserve) or loss of maximum voluntary movement velocity as indicators of proximity to failure (Pelland et al., 2022). Alternatively, practitioners can apply published charts that associate a range of repetition numbers with the respective maximum load relative to the individual 1-RM (Chapman et al., 1998; Mayhew et al., 1993). Typically, the relative loads listed in these "repetition maximum tables" are point predictions based on statistical models that describe relative load as a function of the number of repetitions performed to momentary failure (RTF). Importantly, all the above-mentioned methods of controlling proximity to failure underlie considerable limitations. For example, autoregulative methods using perception of effort have been shown to yield lower accuracy for predicted proximity to failure when sets are terminated far from failure, especially at lighter loads (Halperin et al., 2021). Velocity-based methods, on the other hand, require access to respective monitoring technology and succumb to within-subject variability in movement velocity (Grgic et al., 2020) as well as potential random measurement error introduced by the applied technology (Courel-Ibáñez et al., 2019). Furthermore, published repetition maximum tables generalize the strength-endurance relationship across individuals, in spite of numerous studies providing evidence that the maximum number of repetitions performed at a given relative load increasingly varies between individuals (Desgorces et al., 2010; Mitter et al., 2022b; Richens and Cleather, 2014) and exercises (Hoeger et al., 1990; Shimano et al., 2006), as relative load decreases.

A potential solution to these limitations has been considered by modeling the relationship between load and RTF on an individual level based on multiple sets performed to momentary failure (i.e., trials) at different loads, which allows for repetition maximum tables to be individualized (Dinyer et al., 2019; Morton et al., 2014). Recently, a study performed by our group has provided evidence that the between-subject variance in RTF completed can be explained by inter-individual differences in the strength-endurance relationship, supporting the concept of individual strength-endurance profiles (Mitter et al., 2022b). In this study, four different model functions were tested to represent the strength-endurance relationship in the pin press exercise, including linear regression, two different exponential regression models and the 3-parameters critical load model. Among these models, the 2-parameters exponential regression was identified as the most valuable representation of the strength-endurance relationship, as it provides a good fit and predictive validity while yielding robust parameter estimates across test-retest trials (Mitter et al., 2022a; Mitter et al., 2022b). Importantly, in the above-mentioned studies, data were acquired in the form of a single-visit protocol, meaning that each participant completed trials at three different loads within a single session, and with extended rest intervals between trials. Furthermore, trials with different loads were completed in a standardized order of declining loads to minimize the expected effect of accumulated fatigue. While this approach may be a time-efficient solution to acquire data, it differs considerably from earlier studies that randomly distributed trials across multiple days (i.e., multi-visit protocols), having participants complete only a single trial per session with at least 24 h between sessions (Dinyer et al., 2019; Morton et al., 2014). Differences in achieved performance during single-visit protocols compared to multi-visit protocols have repeatedly been investigated for disciplines such as cycling and running (Galbraith et al., 2014; Karsten et al., 2017; Triska et al., 2021). However, the transferability of those findings to resistance training is questionable, as it can be assumed that different factors contribute to the development of fatigue in resistance exercise compared to endurance exercise. Consequently, participants undergoing a single-visit protocol for the assessment of strength-endurance data may not perform each trial under rested conditions, despite the application of strategies to minimize the expected effect of fatigue between trials (Mitter et al., 2022b). In particular, it can be hypothesized that when applying a fixed order of trials with declining loads, the performance during consecutive sets to momentary failure at lighter loads may be biased negatively and allow for fewer repetitions to be completed than would be possible in a fully rested state (Salles et al., 2009).

Two objectives were defined for the design of the present experiment. First, we aimed to evaluate differences between a fixed-order single-visit (SV) protocol and a random-order multi-visit (MV) protocol for the acquisition of strength-endurance data. Second, we challenged the robustness of the findings from the previously described study (Mitter et al., 2022b), by replicating its analysis of different model types with the data collected during the MV protocol. Apart from the four originally investigated model functions, we also included a reciprocal regression model as a nonlinear alternative to the 2-parameters exponential model with an identical number of parameters, to evaluate whether curvilinear functions of an equivalent level of complexity differ in their fit and predictive performance. Both research questions were investigated for the touch-and-go barbell bench press to apply an economically valid, yet similar exercise compared to the referenced study.

METHODS

Experimental procedure

Participants visited the laboratory on five days with inter-session breaks of 48 to 72 h. They were instructed to refrain from vigorous exercise 24 h before each visit and not to consume caffeine or other potentially confounding stimulants 6 h prior to each visit. On their first visit, they underwent basic anthropometric assessment of their body mass using a digital scale (Seca Model 877; SECA GmbH & Co. KG., Hamburg, Germany). Subsequently, they were familiarized with the experimental setup and completed a 1-RM test in the touch-and-go bench press. During the remaining four visits, participants were tested twice for the RTF at 90%, 80% and 70% 1-RM: once in the form of an SV protocol (i.e., all three trials being completed within a single session) and once in the form of a MV protocol (i.e., trials being distributed across three sessions). The experiment was conducted according to a randomized and counterbalanced cross-over design. First, the order of protocol (SV and MV) was randomized and counterbalanced to have an equal number of participants starting with either protocol. Second, the order of trials was randomized and counterbalanced within the MV protocol, to have an approximately even number of participants completing each order of trials. For the SV protocol, trials were completed in a fixed declining order (trial 1: 90% 1-RM, trial 2: 80% 1-RM, trial 3: 70% 1-RM) to conform with the protocol used in our previous studies (Mitter et al., 2022a; Mitter et al., 2022b). The experimental structure is portrayed in Figure 1.

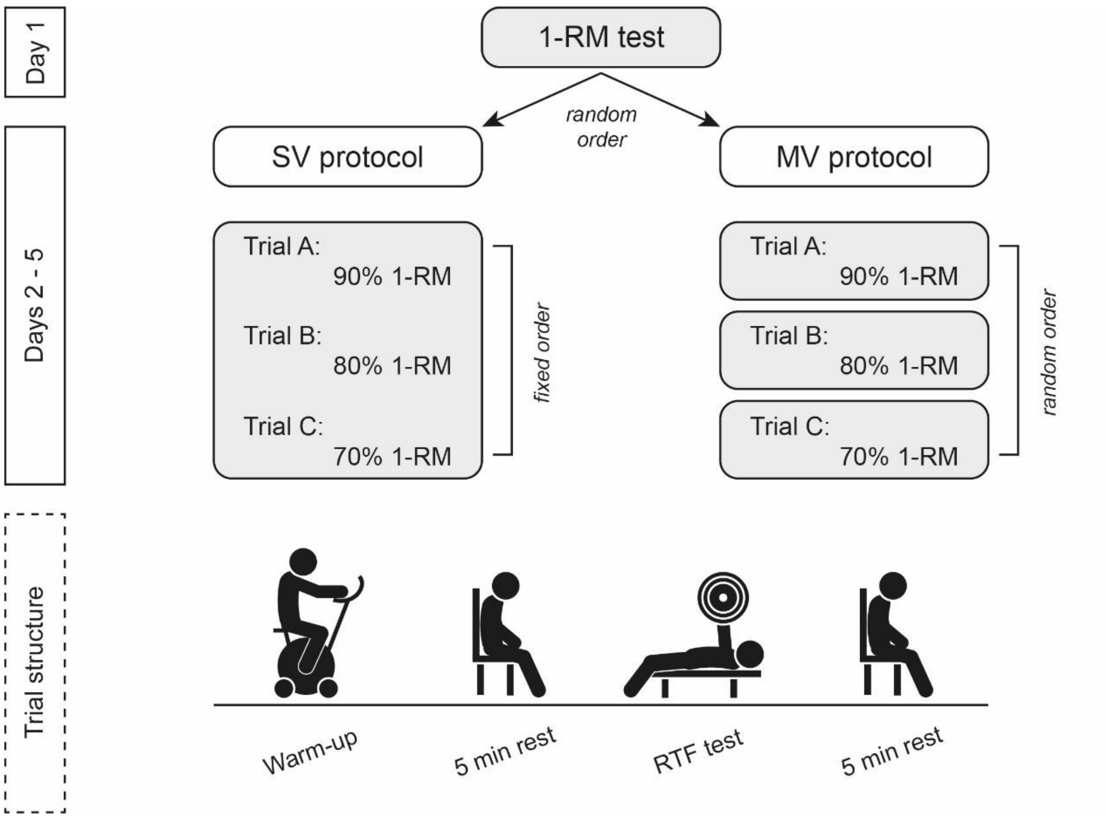

Figure 1. Experimental structure.
1-RM, one-repetition maximum; SV, single-visit; MV, multi-visit; RTF, repetitions performed to momentary failure.

Participants

Fourteen resistance-trained men voluntarily completed the experiment (age: 25.0 ± 2.8 y, body mass: 83.9 ± 8.6 kg, experience in the barbell bench press: 5.9 ± 3.1 y, bench press 1-RM·body mass^{-1}: 1.43 ± 0.22 kg·kg^{-1}). In order to be included in the analysis, applicants were required to fulfill the following criteria: 1) being male and between 18 and 40 years old, 2) being free of acute or chronic illness and musculoskeletal injury, 3) having at least one year of practical training experience in the barbell bench press with regular (at least once a week) application in training, and 4) being able to complete at least one repetition with a load equivalent to their body mass. The satisfaction of criteria 1) through 3) was evaluated by having all applicants complete a modified physical activity readiness questionnaire (PAR-Q) during their first visit to the laboratory, while criterion 4) was evaluated according to the result of the initial 1-RM test. Each participant signed an informed consent form before undergoing physical assessment. The experiment was conducted in compliance with the Declaration of Helsinki and approved by the host institution's local ethics committee (reference number 00727).

Exercise technique and materials

The touch-and-go bench press was executed in a Competition Combo Rack with a standard powerlifting barbell and calibrated weight plates (Eleiko, Halmstad, Sweden). Participants were instructed to lower the barbell in a controlled manner, until it touched their chest, and complete the subsequent concentric movement phase at maximum intended velocity until reaching full extension of their elbow joints on every repetition. They further had to keep their pelvis in contact with the bench and their feet on the floor. An experienced staff member supervised each participant's adherence to the instructions, provided verbal encouragement during sets, and spotted the participant appropriately to ensure safety. A linear position transducer (GymAware Power Tool, Kinetic Performance Technologies, Canberra, Australia) was used to record barbell displacement and velocity during all performed repetitions.

One-repetition maximum test

Prior to the 1-RM test, participants were asked to provide a subjective estimate of their current 1-RM in the touch-and-go bench press. They followed a standardized warm-up including 5 min of stationary cycling at a fixed power output of 1 W per kg body mass and a cadence of 80 rpm (Kettler X1, Tri-sport, Huenenberg, Switzerland). Subsequently, participants completed an initial warm-up set of 10 repetitions at 25% of their estimated 1-RM using a controlled movement cadence. After a 2-min rest, they followed an incremental loading protocol including one set each at 25%, 50%, 75%, 85% and 95% of the estimated 1-RM, using between 1 and 3 repetitions per load and 3 to 5 min of rest in between. The exact number of repetitions and rest duration was autoregulated based on the achieved mean concentric barbell velocity in each set. Following this loading scheme, load increments were selected individually to identify the 1-RM to the closest 2.5 kg increment. A detailed description of the loading protocol and information on its test-retest reliability can be found elsewhere (Mitter et al., 2022a). Participants required (mean ± SD) 2.9 ± 0.9 attempts to reach the 1-RM, achieved 119.6 ± 20.6 kg as a result of the 1-RM test and completed the 1-RM at a mean concentric barbell velocity of 0.13 ± 0.04 $m \cdot s^{-1}$.

Single-visit and multi-visit protocol

The SV protocol was implemented according to a recently described experimental structure (Mitter et al., 2022b). Participants completed three trials within a single session to identify the RTF at 90%, 80% and 70% of the previously determined 1-RM in a fixed declining order of loads. Each trial was initiated by the same general warm-up described for the 1-RM test (i.e., 5 min of stationary cycling). Following this, participants performed one warm-up set of 3x25%, 3x50% and 2x75% 1-RM, respectively, with 3 min of rest in between. 5 min after the last warm-up set, they completed the respective RTF test, followed by another 5 min rest interval, before continuing with the warm-up of the subsequent trial featuring the next lower load. This resulted in a duration of approximately 22 min for each trial, including passive rest. For the RTF test, participants were instructed to complete as many repetitions as possible until reaching momentary failure, while minimizing the time in between repetitions and ensuring that the full range of motion was being used during all repetitions.

In the MV protocol, the three trials described for the SV protocol were distributed across three consecutive sessions with rest periods of 48 to 72 h separating sessions, the order of trials being randomized and counterbalanced across participants. Apart from this, the experimental structure of the applied trials was identical between protocols.

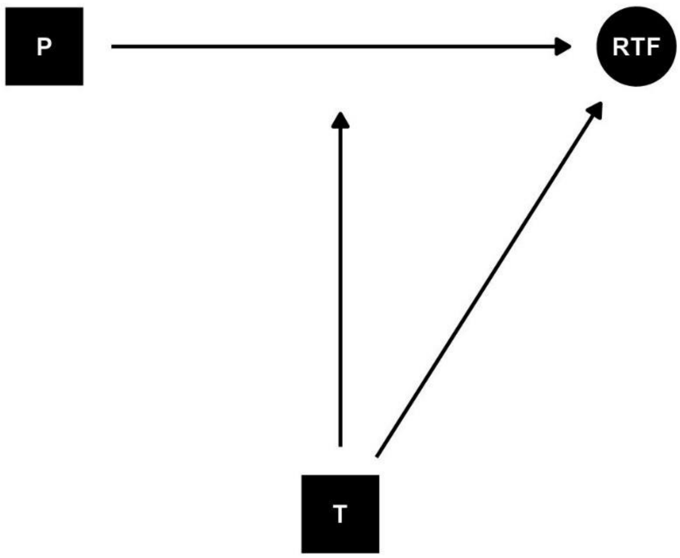

Figure 2. Assumed scientific model (directed acyclic graph).
P, protocol (single-visit, multi-visit); RTF, repetitions performed to momentary failure; T, trial (90%, 80% and 70% of the one-repetition maximum).

Statistical analysis

Both research questions were investigated using an estimation-based Bayesian approach for data analysis, applying the R package rstan (version 2.26.13) in combination with customized Stan scripts (Stan version 2.26.x) to sample from posterior distributions.

To evaluate differences between the SV and MV protocol, a scientific model was constructed based on the main variables of interest and potential covariates. The assumed causal structure is portrayed in Figure 2 as a directed acyclic graph. Based on this structure, a multilevel (i.e., mixed-effects) model with correlated random intercepts and random slopes was defined, applying RTF as a continuous dependent variable, protocol (P) as a binary independent variable and trial (T) as a discrete covariate with three levels, using dummy variables (D_1 and D_2) to express differences between trials. Furthermore, a P x T moderator effect was considered, as potential systematic fatigue during the SV protocol would most reasonably occur only during the 80% and 70% trials, due to the fixed order of trials. The statistical model is expressed in equation 1, random effects being portrayed as bold letters with a subscript "s":

$$\mathrm{RTF} \sim \mathrm{Normal}(\mathbf{a_s} + \boldsymbol{\beta}_\mathbf{s}\, \mathrm{D}_1 + \boldsymbol{\gamma}_\mathbf{s}\, \mathrm{D}_2 + \mathrm{P}\,(\Delta\mathbf{a_s} + \Delta\boldsymbol{\beta}_\mathbf{s}\, \mathrm{D}_1 + \Delta\boldsymbol{\gamma}_\mathbf{s}\, \mathrm{D}_2), \sigma^2) \qquad (1)$$

In equation 1, $\mathbf{a_s}$ describes the performance for the SV protocol in trial A (90% 1-RM), while $\boldsymbol{\beta}_\mathbf{s}$ and $\boldsymbol{\gamma}_\mathbf{s}$ describe the number of *additional* repetitions achieved in trial B (80% 1-RM) and trial C (70% 1-RM) within the SV protocol, respectively. The difference in RTF between the SV and MV protocol for trial A is expressed by $\Delta\mathbf{a_s}$. Finally, $\Delta\boldsymbol{\beta}_\mathbf{s}$ and $\Delta\boldsymbol{\gamma}_\mathbf{s}$ describe the moderator effects of trials B and C on the difference between protocols, and σ^2 yields the variance of model residuals. Zero-centered Cauchy priors were applied for all group-level parameters, group-level standard deviations being limited to positive real numbers. To minimize information introduced by priors, a prior sensitivity analysis was conducted on a set of 5 different prior scales, identifying $Cauchy(0, 5)$ as an appropriate and weakly informative prior choice. Posteriors of group-level parameters were combined to express the difference between SV and MV protocols for each trial in a single posterior, respectively. Subsequently, posteriors were compared against a region of practical equivalence (ROPE) defined at ± 1 repetition, which can be considered the smallest resolution at which differences in RTF can be identified, when only considering repetitions completed across the full range of motion. Effect directions (i.e., negative, trivial or positive) that were supported by at least 95% of posterior probability were deemed "likely". Posterior predictive distributions (PPDs) were calculated for the effect of protocol in each trial to estimate a between-subject standard deviation of expected differences between protocols, accounting for both uncertainty in parameter estimates and sampling uncertainty. Standard deviations were calculated by moment-matching PPDs to normal distributions using the R package fitdistrplus (version 1.1-8).

To compare different model types of the strength-endurance relationship, the analysis described by Mitter et al. (2022b) was replicated using the data acquired during the MV protocol, applying a few analytical adaptations. Data on absolute load and RTF was fitted to linear regression (Lin), 2-parameters exponential regression (Ex2), 3-parameters exponential regression (Ex3) and the critical load model (Crt). Additionally, a reciprocal regression model (Rec) was included in the analysis according to the following function:

$$\text{load} \sim \text{Normal}(1/(\mathbf{a_s} + \text{RTF}\ \mathbf{b_s}), \sigma^2) \tag{2}$$

While the reciprocal regression model is not explicitly addressed in empirical research on the strength-endurance relationship, it is a simple nonlinear adaptation of the linear regression model that applies the same number of parameters as Lin and Ex2 and therefore constitutes a valuable alternative for investigation.

Models were fitted to standardized data as multilevel models with subject-level parameters being sampled from multivariate normal distributions to account for potential correlations between parameters. As for the main analysis, weakly informative priors were identified based on a prior sensitivity analysis. Models were then compared based on variance explained (R^2) and leave-one-out cross-validation information criterion (LOOIC) using the R package loo (version 2.5.1). Differences in R^2 posterior distributions were deemed “likely” if they overlapped less than 5% ($\cap R^2 < 5\%$). Differences in LOOIC (ΔLOOIC) were deemed “likely” if they exceeded 4x the standard error of difference (SE_{Δ}).

Posteriors were summarized using the posterior mean and 95% Highest Density Interval (HDI). All digital materials, including R and Stan scripts, were uploaded to a publicly accessible repository to provide further details on the statistical modeling, Bayesian sampling and the prior sensitivity analysis (https://doi.org/10.5281/zenodo.7190009).

RESULTS

Single-visit vs. multi-visit protocols

Group-level means for RTF completed in the SV protocol were estimated at (mean [95% HDI]) 4.8 repetitions [4.1, 5.5] for trial A (90% 1-RM), 9.4 repetitions [8.5, 10.3] for trial B (80% 1-RM) and 14.3 repetitions [12.9, 15.7] for trial C (70% 1-RM). Posterior distributions of mean differences in RTF completed in the MV and SV protocol for trials A, B, and C (i.e., $\mu_{\Delta a}$, $\mu_{\Delta b}$ and $\mu_{\Delta c}$, respectively) are shown in Figure 3. Analysis revealed likely trivial differences between MV and SV of 0 repetitions [-0.7, 0.7] in trial A [$p(\mu_{\Delta a} \in \text{ROPE} \mid \text{data})$ = 99.3%]. Differences between MV and SV were statistically inconclusive in trial B (0.4 repetitions [-0.4, 1.3]) at the predetermined probabilistic threshold, although posterior analysis revealed a high probability for a trivial effect magnitude [$p(\mu_{\Delta b} \in \text{ROPE} \mid \text{data})$ = 91.8%]. RTF in trial C were found to be likely higher in the MV protocol compared to the SV protocol [$p(\mu_{\Delta c} > \text{ROPE} \mid \text{data})$ = 97.0%], with an estimated mean of 1.9 repetitions [0.9, 2.7]. PPDs yielded between-subject standard deviations of expected differences in trials A, B and C of 0.7, 1.0 and 1.2 repetitions, respectively.

Comparison of strength-endurance models

Statistics for the comparison of different model types are summarized in Table 1. All models fitted the data well and differences between R^2 estimates were statistically inconclusive at the predetermined threshold among all comparisons ($\cap R^2$ = 12.0% - 91.4%). ΔLOOIC estimates indicated that the predictive accuracy was likely worse for Lin compared to Rec and Ex3. Ex2 and Crt also resulted in lower LOOIC estimates (i.e., better predictive performance) when compared to Lin, however, differences did not exceed the predefined threshold (Lin vs. Ex2 and Lin vs. Crt, respectively: ΔLOOIC = 3.7x SE_{Δ}). No clear differences in LOOIC were identified among nonlinear models.

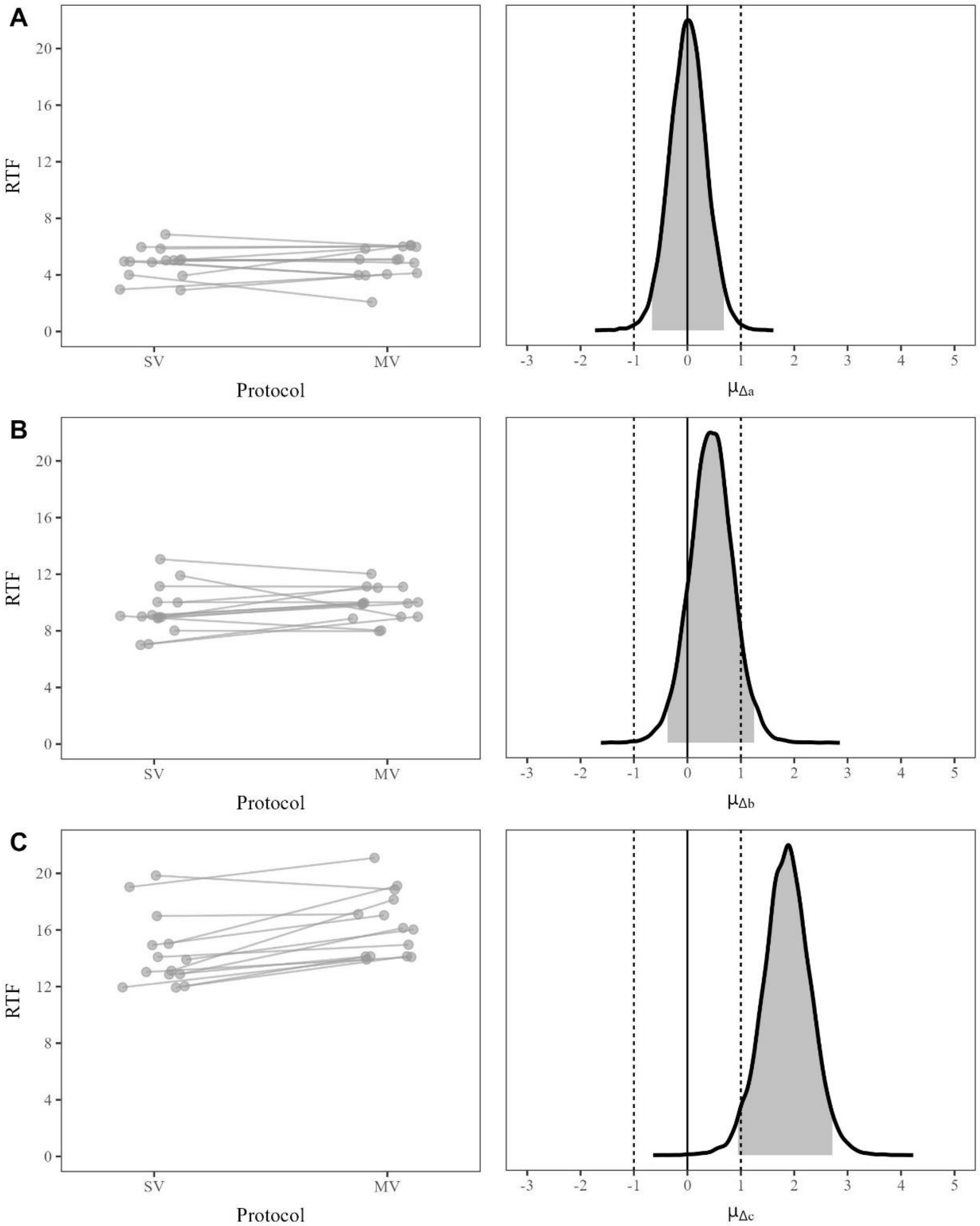

Figure 3. Differences between protocols.

The left column displays observed individual differences (jittered illustration). The right column displays posterior distributions of mean differences in RTF (μ_Δ) achieved in the two protocols (positive numbers indicate more repetitions being performed in the MV protocol). Dashed lines mark a region of practical equivalence defined at [-1, 1] repetitions. The grey area under the curve marks the 95% Highest Density Interval. A, 90% one-repetition maximum; B, 80% one-repetition maximum; C, 70% one-repetition maximum; RTF, repetitions performed to momentary failure; SV, single-visit protocol; MV, multi-visit protocol.

Table 1. Comparison of model fit and predictive performance of five model functions representing the strength-endurance relationship.

Rank	Model	R^2 [95% HDI]	$\cap R^2$ (%)	ΔLOOIC (SE_Δ)
1	Rec	0.99 [0.98, 0.99]		
2	Ex3	0.99 [0.98, 0.99]	82.9	6.7 (11.2)
3	Crt	0.99 [0.98, 0.99]	91.4	12.5 (13.4)
4	Ex2	0.98 [0.97, 0.99]	59.7	22.6 (12.5)
5	Lin	0.97 [0.96, 0.98]	20.3	44.0 (10.9) *

Models are ranked based on LOOIC (smaller values indicating better models).
R2, coefficient of determination (posterior mean); HDI, Highest Density Interval; ∩R2, overlap of R2 posterior distributions with the highest ranked model (Rec); ΔLOOIC, difference in leave-one-out cross-validation information criterion compared to highest ranked model (Rec); SE, standard error of LOOIC differences (* indicating statistically clear differences) ; Rec, reciprocal model; Ex3, 3-parameters exponential model; Crt, critical load model; Ex2, 2-parameters exponential model; Lin, linear regression model.

DISCUSSION

The present study compared two previously described approaches of assessing data for individual strength-endurance profiles: a SV protocol, where multiple sets are performed to failure in a single session with different loads being tested in a fixed order of trials, and a MV protocol, where sets with different loads are distributed across multiple sessions with a randomized order of trials. Moreover, five different model functions were fitted to strength-endurance data acquired during the MV protocol and compared in terms of model fit and predictive performance, to evaluate whether recently published findings based on SV protocols hold true under MV conditions.

To the knowledge of the authors, this is the first study to compare a single-visit to a multi-visit approach for the assessment of strength-endurance at multiple loads. Results indicate that the two protocols likely yield an equivalent number of RTF at 90% 1-RM, which may be attributed to the SV protocol being completed in a fixed declining order of loads. Hence, the trial at 90% 1-RM was completed under approximately identical within-session conditions in both protocols. Similarly, the difference between protocols for the trial performed at 80% 1-RM suggested a high probability for practical equivalence, although the effect was not deemed clear at the predefined probabilistic threshold. Finally, analysis revealed that the MV protocol likely allows for a larger number of RTF to be performed for the 70% 1-RM trial, compared to the SV approach. Therefore, it could be hypothesized that while the SV protocol provided participants an extended rest period in between sets performed to failure, this rest period may not have sufficiently compensated fatigue that accumulated during the first two trials of the SV protocol. In general, these findings agree with previous studies showing a loss in repetition performance over repeated sets performed to failure or close to failure (García-López et al., 2008; Iglesias-Soler et al., 2012; Miranda et al., 2009; Ratamess et al., 2012; Salles et al., 2009; Santos et al., 2021; Senna et al., 2009). However, since these effects were shown to be moderated by rest duration in between sets, with longer rest periods allowing for a better retention of repetition performance, it is surprising that repetition performance was not recovered during the 22 min in between RTF tests. Richmond and Godard (2004) reported that under rested conditions, participants were able to complete 11.5 ± 2.3 repetitions in the bench press performed at 75% 1-RM, whereas they could only complete an average 9.8 ± 2.0 repetitions in a second set performed after 5 min of rest [i.e., statistics were synthesized from a figure using WebPlotDigitizer (Rohatgi, 2020)]. The average loss in performance of 1.7 repetitions corresponds well to the loss in performance identified in the last trial of the SV protocol during the present study (mean [95% HDI] = 1.9 repetitions [0.9, 2.7]), although Richmond and Godard (2004) provided only about a quarter of the inter-set rest time used in the present investigation. While it cannot be ruled out that the loss in performance observed in the SV protocol may be partially explained by applied measures to maintain warm-up effects, it can be speculated that the effect may be attributed to a component of fatigue that persists beyond 22 min of rest. Various physiological pathways may contribute to the explanation of the observed effects, including the incomplete degradation of metabolites, such as ammonia (Morán-Navarro et al., 2017) and inorganic phosphate (Feriche et al., 2020), as well as central fatigue processes. However, a comprehensive discussion of potential mechanisms is beyond the scope of the present article. Interested readers are referred to other sources for information (Kataoka et al., 2022; Zając et al., 2015).

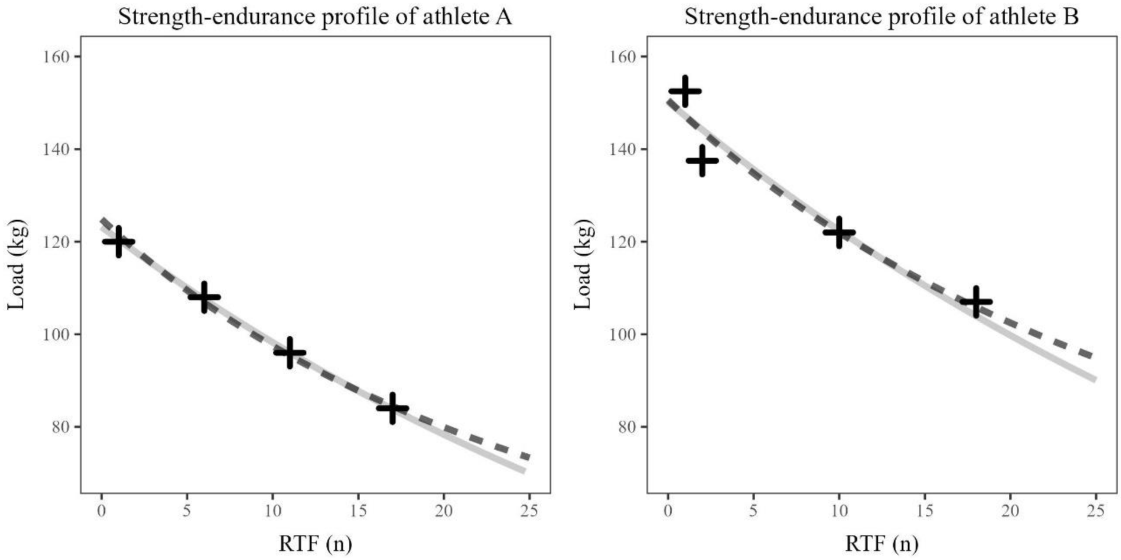

Figure 4. Examples for strength-endurance profiles.
Data were taken from the individual showing the best model fit (A, left panel) and the one showing the worst model fit (B, right panel). Black crosses display subject data. Solid lines display the exponential 2-parameters model fits. Dashed lines display the reciprocal regression model fits.
RTF, repetitions performed to momentary failure.

Since the present study provides evidence that the SV protocol succumbs systematic negative bias in the third trial completed at 70% 1-RM, it is questionable whether the strength-endurance relationship is indeed best represented by the 2-parameters exponential regression model, as recently reported (Mitter et al., 2022b). Interestingly, the analysis of the proposed model functions revealed similar results compared to the referenced study: Lin showed the worst model fit as indicated by R^2 estimates among investigated models, however, differences were not statistically conclusive at the predefined threshold. Similarly, Lin yielded the worst predictive performance as indicated by LOOIC, with estimates being likely different to Rec and Ex3 and closely approaching the threshold of likely differences for Ex2 and Crt. These findings conform to what would be expected from a logical perspective: if the SV protocol biases the lower-load end of the strength-endurance relationship negatively, but is nevertheless well represented by curvilinear functions, the trend will most likely not be linear under a MV protocol, where the relationship is shifted towards higher repetition numbers at lower loads. Similar to our earlier findings (Mitter et al., 2022b), the analysis did not reveal a statistically conclusive difference of R^2 and LOOIC estimates among curvilinear model types. Importantly, the reciprocal model (Rec) proposed in the present study was found to be a valuable alternative to other curvilinear models. While the model has not been addressed in empirical research thus far, it can be rearranged from a few proposed equations used to predict the 1-RM from RTF at submaximal loads, such as the ones associated with Brown (1992), O'Connor et al. (1989) or Welday (1988) [for review, see Mayhew et al. (2008)]. The function further allows for a simple estimation of model parameters by first applying a reciprocal transformation to load (i.e., 1/load) and then fitting a common linear regression model to estimate parameters. In accordance with our recently communicated analytical approach (Mitter et al., 2022b), Ex2 and Rec provide the most appropriate representations of the strength-endurance relationship (Figure 4), as they yield a similar fit and predictive accuracy compared to Ex3 and Crt, while relying on fewer parameters. Additionally, recent research has shown that parameter estimates for Ex3 and Crt vary noticeably over the course of one week, flagging them as non-robust functions (Mitter et al., 2022a).

CONCLUSION

The results of the present study provide evidence that when assessing strength-endurance (RTF) in the bench press at 90%, 80% and 70% 1-RM by following a single-visit protocol with a declining order of loads, performance at 70% 1-RM is likely biased negatively. In particular, performance at 70% 1-RM can be expected to be reduced by (PPD mean ± SD) 1.9 ± 1.2 repetitions when RTF tests are completed 22 min apart. Practitioners who want to assess multiple instances of strength-endurance, for example for the computation of individual strength-endurance profiles, are therefore advised to embed RTF assessments across multiple consecutive training sessions, preferably at the beginning of each session, following a standardized warm-up. When computing strength-endurance profiles based on such data, practitioners should rely on simple curvilinear model functions, such as the reciprocal regression model or the 2-parameters exponential regression model.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the participants who contributed to the present study. Furthermore, we would like to thank Intelligent Strength Education GmbH for providing each participant with free goods as a reward for their participation.

The authors have no professional relationships with companies or manufacturers mentioned in the present study and no financial support from third parties was received for its execution. There is no conflict of interest to declare. Experiments were conducted in compliance with the current laws of the country in which they were performed.

DISCLOSURE STATEMENT

There is no conflict of interest to declare. Experiments were conducted in compliance with the current laws of the country in which they were performed.

REFERENCES

Brown, H.L. (1992) *Lifetime fitness*. 3rd edition. Scottsdale, Ariz.: Gorsuch Scarisbrick.

Chapman, P.P., Whitehead, J.R. and Binkert, R.H. (1998) The 225–1b Reps-to-Fatigue Test as a Submaximal Estimate of 1-RM Bench Press Performance in College Football Players. *Journal of Strength and Conditioning Research* **12(4)**, 258–261.

Courel-Ibáñez, J., Martínez-Cava, A., Morán-Navarro, R., Escribano-Peñas, P., Chavarren-Cabrero, J., González-Badillo, J.J. and Pallarés, J.G. (2019) Reproducibility and Repeatability of Five Different Technologies for Bar Velocity Measurement in Resistance Training. *Annals of biomedical engineering* **47(7)**, 1523–1538.

Desgorces, F.D., Berthelot, G., Dietrich, G. and Testa, M.S.A. (2010) Local muscular endurance and prediction of 1 repetition maximum for bench in 4 athletic populations. *Journal of Strength and Conditioning Research* **24(2)**, 394–400.

Dinyer, T.K., Byrd, M.T., Vesotsky, A.N., Succi, P.J. and Bergstrom, H.C. (2019) Applying the Critical Power Model to a Full-Body Resistance-Training Movement. *International journal of sports physiology and performance* **14(10)**, 1364–1370.

Feriche, B., Schoenfeld, B.J., Bonitch-Gongora, J., La Fuente, B. de, Almeida, F., Argüelles, J., Benavente, C. and Padial, P. (2020) Altitude-induced effects on muscular metabolic stress and hypertrophy-related factors after a resistance training session. *European journal of sport science* **20(8)**, 1083–1092.

Galbraith, A., Hopker, J., Lelliott, S., Diddams, L. and Passfield, L. (2014) A single-visit field test of critical speed. *International journal of sports physiology and performance* **9(6)**, 931–935.

García-López, D., Herrero, J.A., Abadía, O., García-Isla, F.J., Ualí, I. and Izquierdo, M. (2008) The role of resting duration in the kinematic pattern of two consecutive bench press sets to failure in elite sprint kayakers. *International journal of sports medicine* **29(9)**, 764–769.

Grgic, J., Scapec, B., Pedisic, Z. and Mikulic, P. (2020) Test-Retest Reliability of Velocity and Power in the Deadlift and Squat Exercises Assessed by the GymAware Power-Tool System. *Frontiers in physiology* **11**, 561682.

Halperin, I., Malleron, T., Har-Nir, I., Androulakis-Korakakis, P., Wolf, M., Fisher, J. and Steele, J. (2021) Accuracy in Predicting Repetitions to Task Failure in Resistance

Exercise: A Scoping Review and Exploratory Meta-analysis. *Sports medicine (Auckland, N.Z.)*.

Hickmott, L.M., Chilibeck, P.D., Shaw, K.A. and Butcher, S.J. (2022) The Effect of Load and Volume Autoregulation on Muscular Strength and Hypertrophy: A Systematic Review and Meta-Analysis. *Sports medicine - open* **8(1)**, 9.

Hoeger, W.W., Hopkins, D.R., Barette, S.L. and Hale, D.F. (1990) Relationship between repetitions and selected percentages of one repetition maximum: A comparison between un-trained and trained males and females. *Journal of Strength and Conditioning Research* **4(2)**, 47–54.

Iglesias-Soler, E., Carballeira, E., Sánchez-Otero, T., Mayo, X., Jiménez, A. and Chapman, M.L. (2012) Acute effects of distribution of rest between repetitions. *International journal of sports medicine* **33(5)**, 351–358.

Karsten, B., Hopker, J., Jobson, S.A., Baker, J., Petrigna, L., Klose, A. and Beedie, C. (2017) Comparison of inter-trial recovery times for the determination of critical power and W' in cycling. *Journal of sports sciences* **35(14)**, 1420–1425.

Kataoka, R., Vasenina, E., Hammert, W.B., Ibrahim, A.H., Dankel, S.J. and Buckner, S.L. (2022) Is there Evidence for the Suggestion that Fatigue Accumulates Following Resistance Exercise? *Sports medicine (Auckland, N.Z.)* **52(1)**, 25–36.

Mayhew, J.L., Johnson, B.D., Lamonte, M.J., Lauber, D. and Kemmler, W. (2008) Accuracy of prediction equations for determining one repetition maximum bench press in women before and after resistance training. *Journal of Strength and Conditioning Research* **22(5)**, 1570–1577.

Mayhew, J.L., Ware, J.R. and Prinster, J.L. (1993) Using Lift Repetitions to Predict Msucular Strength in Adolescent Males. *National Strength and Conditioning Association Journal* **15(6)**, 35–38.

Miranda, H., Simão, R., Moreira, L.M., Souza, R.A. de, Souza, J.A.A. de, Salles, B.F. de and Willardson, J.M. (2009) Effect of rest interval length on the volume completed during upper body resistance exercise. *Journal of sports science & medicine* **8(3)**, 388–392.

Mitter, B., Csapo, R., Bauer, P. and Tschan, H. (2022a) Reproducibility of strength performance and strength-endurance profiles: A test-retest study. *PloS one* **17(5)**, e0268074.

Mitter, B., Zhang, L., Bauer, P., Baca, A. and Tschan, H. (2022b) Modeling the Relationship between Load and Repetitions to Failure in Resistance Training: A Bayesian Analysis. *European journal of sport science*, 1–26.

Morán-Navarro, R., Pérez, C.E., Mora-Rodríguez, R., La Cruz-Sánchez, E. de, González-Badillo, J.J., Sánchez-Medina, L. and Pallarés, J.G. (2017) Time course of recovery following resistance training leading or not to failure. *European journal of applied physiology* **117(12)**, 2387–2399.

Morton, R.H., Redstone, M.D. and Laing, D.J. (2014) The Critical Power Concept and Bench Press: Modeling 1RM and Repetitions to Failure. *International journal of exercise science* **7(2)**, 152–160.

O'Connor, R., Simmons, J. and O'Shea, P. (1989) *Weight training today.* St. Paul: West.

Pelland, J.C., Robinson, Z.P., Remmert, J.F., Cerminaro, R.M., Benitez, B., John, T.A., Helms, E.R. and Zourdos, M.C. (2022) Methods for Controlling and Reporting Resistance Training Proximity to Failure: Current Issues and Future Directions. *Sports medicine (Auckland, N.Z.)*.

Ratamess, N.A., Chiarello, C.M., Sacco, A.J., Hoffman, J.R., Faigenbaum, A.D., Ross, R.E. and Kang, J. (2012) The effects of rest interval length on acute bench press performance: the influence of gender and muscle strength. *Journal of Strength and Conditioning Research* **26(7)**, 1817–1826.

Richens, B. and Cleather, D.J. (2014) The relationship between the number of repetitions performed at given intensities is different in endurance and strength trained athletes. *Biology of sport* **31(2)**, 157–161.

Richmond, S.R. and Godard, M.P. (2004) The effects of varied rest periods between sets to failure using the bench press in recreationally trained men. *Journal of Strength and Conditioning Research* **18(4)**, 846–849.

Rohatgi, A. (2020) *WebPlotDigitizer.* Pacifica, CA, USA.

Salles, B.F. de, Simão, R., Miranda, F., Da Novaes, J.S., Lemos, A. and Willardson, J.M. (2009) Rest interval between sets in strength training. *Sports medicine (Auckland, N.Z.)* **39(9)**, 765–777.

Santos, W.D.N.D., Vieira, C.A., Bottaro, M., Nunes, V.A., Ramirez-Campillo, R., Steele, J., Fisher, J.P. and Gentil, P. (2021) Resistance Training Performed to Failure or Not to Failure Results in Similar Total Volume, but With Different Fatigue and Discomfort Levels. *Journal of strength and conditioning research* **35(5)**, 1372–1379.

Senna, G., Salles, B.F., Prestes, J., Mello, R.A. and Roberto, S. (2009) Influence of two different rest interval lengths in resistance training sessions for upper and lower body. *Journal of sports science & medicine* **8(2)**, 197–202.

Shimano, T., Kraemer, W.J., Spiering, B.A., Volek, J.S., Hatfield, D.L., Silvestre, R., Vingren, J.L., Fragala, M.S., Maresh, C.M., Fleck, S.J., Newton, R.U., Spreuwenberg, L.P.B. and Häkkinen, K. (2006) Relationship between the number of repetitions and selected percentages of one repetition maximum in free weight exercises in trained and untrained men. *Journal of Strength and Conditioning Research* **20(4)**, 819–823.

Steele, J., Fisher, J., Giessing, J. and Gentil, P. (2017) Clarity in reporting terminology and definitions of set endpoints in resistance training. *Muscle & nerve* **56(3)**, 368–374.

Suchomel, T.J., Nimphius, S., Bellon, C.R., Hornsby, W.G. and Stone, M.H. (2021) Training for Muscular Strength: Methods for Monitoring and Adjusting Training Intensity. *Sports medicine (Auckland, N.Z.)* **51(10)**, 2051–2066.

Triska, C., Hopker, J., Wessner, B., Reif, A., Tschan, H. and Karsten, B. (2021) A 30-Min Rest Protocol Does Not Affect W', Critical Power, and Systemic Response. *Medicine and science in sports and exercise* **53(2)**, 404–412.

Welday, J. (1988) Should you check for strength with periodic max lifts? *Scholastic Coach* **57(9)**, 49–68.

Zając, A., Chalimoniuk, M., Maszczyk, A., Gołaś, A. and Lngfort, J. (2015) Central and Peripheral Fatigue During Resistance Exercise - A Critical Review. *Journal of human kinetics* **49**, 159–169.

3 Discussion

3.1 Summary

The present thesis explored the strength-endurance relationship to provide practitioners with a valid methodological approach for assessing strength-endurance profiles. For this purpose, we first investigated whether strength-endurance models, which account for individual trends, provide a superior alternative to complete-pooling models, which generalize the strength-endurance relationship across subjects. We then compared different mathematical functions based on their validity (i.e., model fit and predictive accuracy), simplicity (i.e., number of model parameters), and robustness across test-retest trials to determine which function(s) yield the most appropriate representation of the strength-endurance relationship. Lastly, we compared two protocols for assessing strength-endurance data to determine whether RTF tests yield different results when performed in a single session (i.e., single-visit protocol) or distributed across multiple days (i.e., multi-visit protocol). Data acquired during the multi-visit protocol of the final experiment were further used to replicate the analysis of different mathematical functions from the first experiment and, therefore, challenge the robustness of those findings in a new sample. All research questions were addressed in variants of the bench press exercise.

3.1.1 Modeling strength endurance

As demonstrated in publication #1, evidence supports the strength-endurance relationship following individual trends when loads are normalized to the individual 1-RM load (Mitter, Zhang, et al., 2022). When modeling strength endurance with respect to individual trends (i.e., using a multilevel approach), the models accounted for the heteroscedasticity that results from normalizing load. Consequently, the individual modeling approach yielded a better model fit and predictive accuracy than the commonly proposed complete-pooling approach, especially at lower relative loads.

When comparing the capability of different functions to model the association between relative load and RTF, publication #1 provides strong evidence that curvilinear functions are more appropriate than a linear regression model (Mitter, Zhang, et al., 2022). While these findings were based on a methodological approach that applied a single-visit protocol to determine RTF, the replication analysis presented in publication #3 provided additional support for this conclusion under implementing a multi-visit protocol and introducing absolute load instead of relative load as a dependent variable (Mitter, Raidl, et al., 2022). While the original analysis in publication #1 only featured four functions (i.e., Lin, Ex2, Ex3, and Crt), the replication analysis presented in publication #3 further included a reciprocal regression model (Rec). To the author's knowledge, this model has not been explicitly covered in experimental research thus far and can only be reformulated from particular 1-RM prediction equations with unclear scientific background (see section 1.2.2.1). However, the inclusion of Rec in the replication analysis yielded an interesting methodological step to challenge the ranking of Ex2. Indeed, in publication #1, Ex2 was considered the most appropriate model because it relies on fewer parameters than Ex3 and Crt. As such, adding another curvilinear function with an equal number of parameters to the list of investigated models was considered a valuable analytical improvement. Interestingly, Rec yielded a similar model fit and predictive accuracy compared to Ex2, indicating that it is a valid alternative to model the individual strength-endurance relationship.

The relevance of a specific model for application in a practical setting is not solely determined by its capacity to fit and predict data. It is also determined by the robustness of parameter estimates during a short time frame when changes in observed scores are expected to be predominantly the result of biological noise. Publication #2 investigated this using a test-retest study design and demonstrated that models including three parameters (i.e., Ex3 and Crt) succumbed to large variations in parameter estimates, even though changes in performance were only trivial (Mitter, Csapo, et al., 2022). On the other hand, models applying two parameters (i.e., Lin and Ex2) resulted in more robust estimates, as indicated by the relative and standardized magnitude of change effects. It can be hypothesized that while Ex3 and Crt feature high flexibility to fit the observed data, there may be a broad spectrum of parameter combinations resulting in an equivalent model fit for the range of observed data. This notion is illustrated in Figure 9, which shows that considerable differences in parameter estimates for Crt may still yield similar trends for a given segment of the strength-endurance continuum. Hence, it may be assumed that Ex3 and Crt introduce a structural complexity that impedes the estimation of model parameters in the load range of 70% to 100% 1-RM. Also, the flexibility of Ex3 and Crt to fit data may promote overfitting of the biological noise and, thus, result in non-robust parameter estimates across test-retest trials.

Importantly, publication #2 did not include the reciprocal regression model, as it focused on functions explicitly proposed in previous research. However, an unpublished retrospective reanalysis of Rec applying the same data and analytical workflow from publication #2 revealed that the function yields similar robustness compared to Lin and Ex2. A summary of the robustness analysis of Rec is available in Table 4.

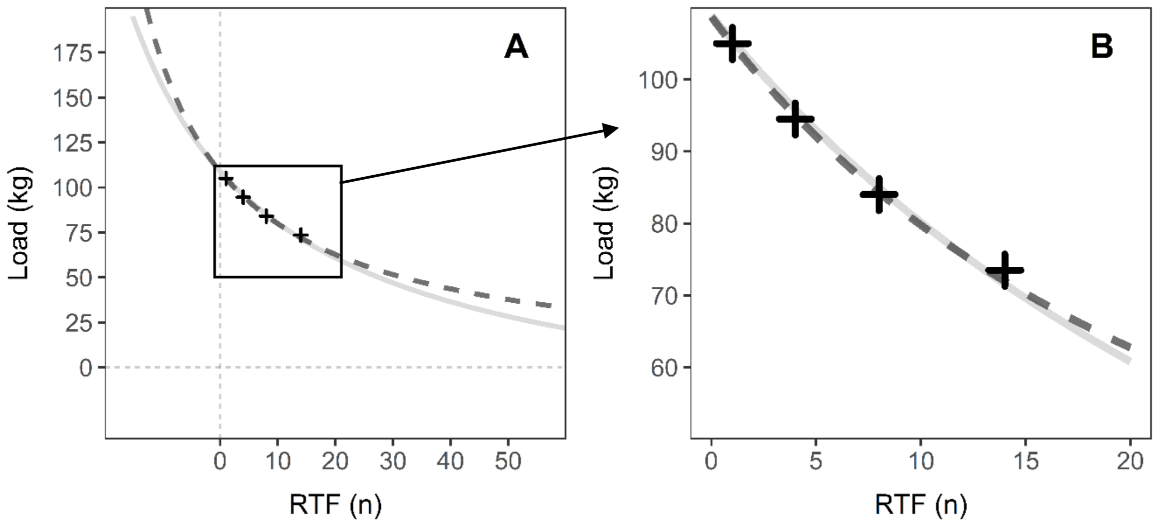

Figure 9. The critical load model fitted with two heterogeneous sets of parameters. Panel B displays a close-view segment of panel A. The black marks display observed data. The solid line displays a model fit with parameters L' = 6045, k = -41.1, and CL = -38.1, whereas the dashed line displays a model fit with parameters L' = 3188, k = -28.6, and CL = -2.9. The light grey dotted lines indicate the coordinates y = 0 and x = 0. RTF, repetitions performed to momentary failure.

Table 4. Summary of posterior predictive distributions of relative and standardized change effects (supplemental analysis to publication #2)

Model	**Change effect**	**Relative magnitude (%) ***	**Standardized magnitude ****	**p ($\Delta x_i \in$ [-0.6, 0.6] | data) ****
Rec	Δa	-0.6 [-2.2, 1.2]	-0.9 [-8.18, 4.55]	26.7 %
	Δb	-4.8 [-19.4, 8.4]	-0.22 [-0.83, 0.38]	84.0 %

Posterior predictive distributions are summarized using the Maximum a Posteriori estimate and 90% Highest Density Interval.

*, change effects are expressed relative to the group-level mean of the associated model parameter at T1.

**, change effects are standardized to the group-level standard deviation of the associated model parameter at T1.

Rec, reciprocal regression model; p ($\Delta x_i \in$ [-0.6, 0.6] | data), probability of the standardized change effect falling within the threshold for acceptable differences given the data.

In summary, Ex2 and Rec yielded a valid representation of the strength-endurance relationship, robust parameter estimates, and a simple mathematical structure compared to Ex3 and Crt. Figure 10 displays the investigated functions when mapped qualitatively to the discussed criteria.

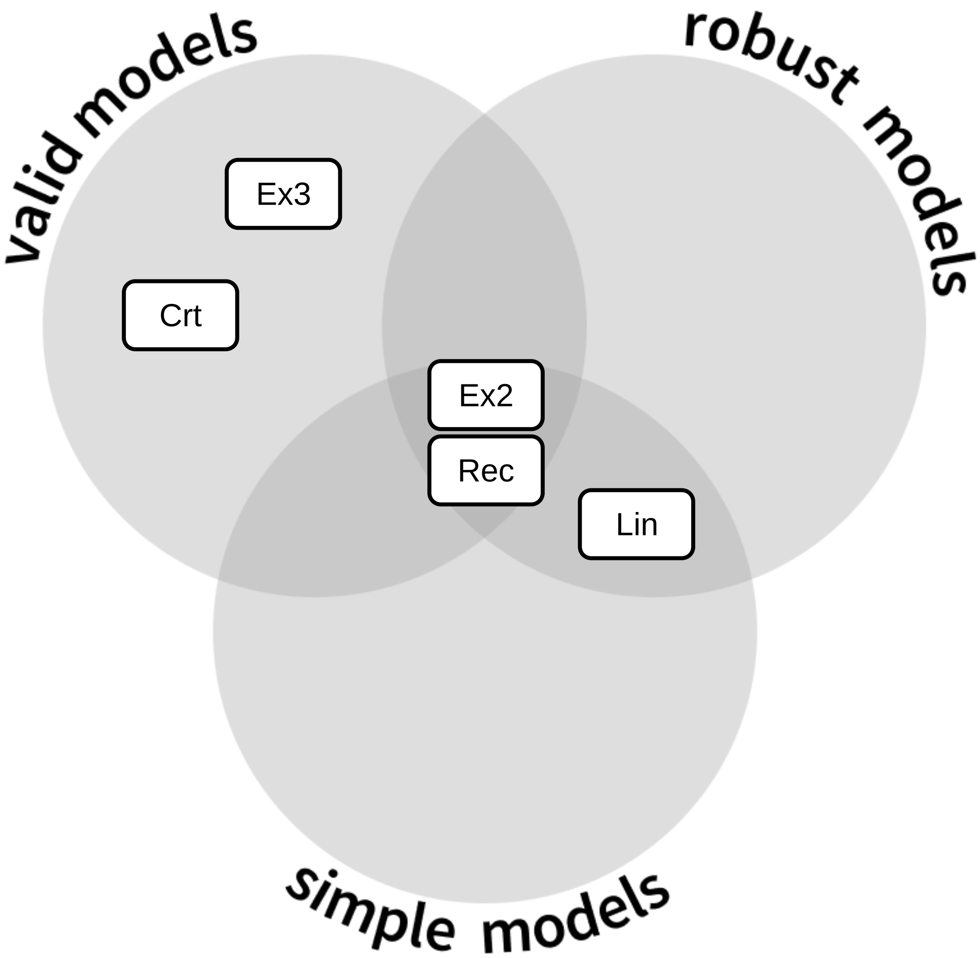

Figure 10. Summary of the comparison between the investigated model functions. Model validity was evaluated based on model fit and predictive accuracy. Model robustness was evaluated based on changes in model parameters across test-retest trials. Model simplicity was evaluated based on the number of model parameters. Crt, critical load model; Ex2, exponential model (2 parameters); Ex3, exponential model (3 parameters); Lin, linear model; Rec, reciprocal model.

3.1.2 Data acquisition for strength-endurance profiles

Publication #3 provides evidence that strength-endurance performance is substantially impaired in later trials when RTF are assessed at 90%, 80%, and 70% 1-RM within a single session, even when a long recovery period is applied between trials (Mitter, Raidl, et al., 2022). Although the fixed order of loads applied in the SV protocol does not enable any conclusions about alternative single-visit designs, using a different order would likely have resulted in a similar or even greater impairment on RTF performance, given that fatigue is typically more pronounced after sets performed to failure at lower relative loads (Salles et al., 2009; Sánchez-Medina & González-Badillo, 2011). Overall, it can be concluded that, on average, distributing RTF tests across multiple days yields less biased data for the computation of strength-endurance profiles. Thus, the application of a multi-visit protocol for strength-endurance data acquisition is warranted.

3.2 Practical Applications

The relationship between load and the number of RTF on any exercise can be quantified by determining an individual's strength-endurance profile, which can be established based on the absolute (kg, lbs) or the relative (%1-RM) load applied. Based on these profiles, practitioners and researchers can prescribe and control set-repetition schemes with respect to the intensity of effort, and describe changes in strength endurance across a broad range of loads. Unfortunately, the mathematical knowledge underlying the modeling of such profiles typically hinders the application of these concepts to the daily practice of professionals. In that regard, practitioners can now conveniently determine individual strength-endurance profiles through a user-friendly web application developed alongside the current dissertation project (Mitter, 2022). The app is freely accessible through the link "https://strength-and-conditioning-toolbox.shinyapps.io/Strength-Endurance_Profile/", previously made available in Publication #2 (Mitter, Csapo, et al., 2022). We expect this to facilitate the use and dissemination of strength-endurance profiling within the field of resistance training.

Ex2 and Rec have been identified as the best approximations of the strength-endurance relationship among investigated models. These model functions can be easily fitted as bivariate linear regression models after applying the appropriate transformation to load as the dependent variable. Specifically, a reciprocal transformation for Rec and a natural log transformation for Ex2 is necessary, as detailed in section 8.1, Appendix A. In either case, it is essential to note that at least three RTF tests must be conducted for an error term to be established.

3.2.1 Strength-endurance profiles as *descriptive* tools

Absolute strength-endurance profiles can be used as a comprehensive description of an athlete's fatiguability across a broad range of loads. Thus, they may be applied to quantify whether systematic changes in local muscular endurance are consistent across various loads or if changes have been more pronounced at either end of the spectrum. For the exponential 2-parameters model investigated, the magnitude of consistent changes can be evaluated based on changes in the intercept parameter *a*, whereas changes in the curvature parameter *b* mark specific changes. For example, considering an absolute strength-endurance profile with estimated parameters of {*a* = 102, *b* = -0.03} at baseline, a training-induced change of the intercept by ten units to {*a* = 112} with an unchanged curvature *b* would indicate that the respective individual improved their local muscular endurance consistently by about 3 repetitions across the load spectrum (Figure 11).

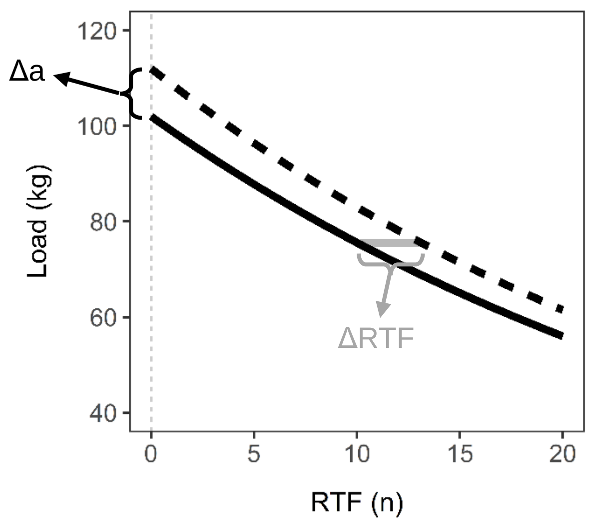

Figure 11. Quantifying consistent changes in strength endurance using model parameters. Strength-endurance profiles were calculated using the exponential 2-parameters function. The solid black line represents a profile with parameters {a = 102, b = -0.03}. The dashed black line represents a profile with an increased intercept a = 112 but an equivalent magnitude of b. The dashed grey line represents the load axis at RTF = 0. The solid grey line represents the change in strength endurance (ΔRTF ≈ 3.12 repetitions), which is consistent across the full spectrum. Δa, change in model intercept; RTF, repetitions performed to momentary failure.

The formula used to estimate this consistent change in strength endurance (ΔRTF) based on the value of the model parameters at baseline (*a*, *b*) and the corresponding change in the intercept (*Δa*) can be mathematically expressed as follows:

$$\Delta RTF = \frac{1}{b} ln\left(\frac{a}{a + \Delta a}\right) \tag{32}$$

A derivation of eq. 32 is provided in section 8.3 (Appendix C).

3.2.2 Strength-endurance profiles as *predictive* tools

Strength-endurance profiles can also be used to predict the load associated with a given repetition maximum in rested conditions. In this case, exercise- and subject-specific repetition maximum tables can be generated using a series of RTF values in the appropriate relative strength-endurance profile predictive equation. This feature is also included in the openly accessible web application and can be easily determined using the results of three different RTF tests (Mitter, 2022). However, generated tables only provide point predictions based on the estimated model, and thus, observed values may deviate from predicted ones due to the uncertainty of estimates and biological noise. It can also be expected that if values are extrapolated to loads distant from the ones on which the model is based on, such predictions will be less precise, as illustrated in Figure 4.D (Hahn, 1977). Hence, practitioners should intentionally apply the RTF tests at loads in the range intended for predictions.

As described in section 1.2.2.2, predictions can be further applied to normalize effort using methodological approaches such as RI_{SR} or RE_v. In the present thesis, we identified the linear regression model as an inadequate approximation to the strength-endurance relationship in the range of 70% to 100% 1-RM. As a consequence, the formula for RE_v proposed in eq. 31 is likely biased. Here, we propose an adaptation to the original RE_v equation based on individual strength-endurance profiles using Ex2 as a model function:

$$RE_v = \varphi = \frac{|\overrightarrow{OA}|}{|\overrightarrow{OS}_{max}|} = \frac{load_a}{load_{lim}} = \frac{n_a}{n_{lim}} = -b\, n_a\, W_0\left(-\frac{a\, b\, n_a}{load_a}\right)^{-1} \tag{33}$$

In eq. 33, n_a and $load_a$ represent the number of repetitions performed and the load used on a given set, respectively. Further, *a* and *b* represent the parameters of the exponential strength-endurance profile, and $W_0(x)$ represents the Lambert *W* function for $x \geq 0$ (principal branch). $W_0(x)$ can be calculated using various open-source solutions, such as the *lambertWp* function from the R package *pracma*. The derivation of eq. 33 is available in section 8.4 (Appendix D).

Alternatively, those preferring Rec as a model function for strength-endurance profiles can calculate RE_v according to the following equation:

$$RE_v = \varphi = \frac{|\overrightarrow{OA}|}{|\overrightarrow{OS}_{max}|} = \frac{load_a}{load_{lim}} = \frac{n_a}{n_{lim}} = 2\ b\ n_a \left(\sqrt{a^2 + \frac{4\ b\ n_a}{load_a}} - a \right)^{-1} \qquad (34)$$

The derivation of eq. 34 is available in section 8.5 (Appendix E). To facilitate the computation of RE_v based on strength-endurance profiles for practitioners, developers of mobile applications for resistance training documentation should consider to create machine learning algorithms that autonomously compute and adapt strength-endurance profiles based on training log data, and incorporate respective RE_v equations as a monitoring feature.

3.3 Limitations

The experimental procedures conducted in this thesis are not exempt from limitations. Although most of them have already been addressed in the published manuscripts, certain limitations must also be acknowledged here. Thus, the following sections will provide an overview of these limitations and discuss their impact on the main findings.

3.3.1 Participants

All experiments were conducted with samples of resistance-trained individuals. The respective inclusion criteria that determined this (i.e., minimal required training experience and minimal 1-RM performance in the bench press) were implemented for two reasons. First, it was considered that experienced participants would be less susceptible to injury during sets performed to momentary failure, as practice time has previously been shown to be inversely associated with injury rate (Kemler et al., 2022; Sprey et al., 2016). Moreover, it was assumed that resistance-trained individuals would experience less systematic performance changes over a test-retest protocol due to being more familiarized with the exercise technique (Cronin & Henderson, 2004; Ritti-Dias et al., 2011). This experience may be considered a prerequisite for assessing strength-endurance profiles because they assume an absence of systematic changes during data acquisition to describe a cross-sectional performance state. Consequently, the findings of the present thesis may not directly apply to different populations, including untrained individuals. Practitioners and researchers should be wary of potential bias resulting from systematic changes in performance during data acquisition when estimating strength-endurance profiles for novice lifters.

3.3.2 Exercise

Every experiment designed for the present thesis included a variant of the free-weight bench press exercise, mainly because it represents a compound exercise that, compared to other resistance exercises, facilitates the precise determination of a set endpoint due to momentary failure. For reference, potential difficulties in identifying the point of momentary failure have been discussed for different exercises in section 1.1.2. Publications #1 and #2 applied a variant of the bench press occasionally labeled "pin press", which involves a dead stop at the end of the eccentric movement phase, where the barbell briefly rests on two safety pins. Subsequently, the concentric movement phase was initiated upon a verbal command provided by a staff member. These restrictions were applied to cancel out expected irregularities in the range of motion, to exclude a contribution of the stretch-shortening cycle or "bouncing" of the barbell as a source of variance, and to provide participants with a safe experimental environment during sets performed to failure. Publication #3 applied the touch-and-go bench press (i.e., without verbal commands) as an alternative exercise variant that allows participants to use the stretch-shortening cycle. Regulations about the exercise technique were loosened for this final experiment to investigate whether recent findings hold under less restrictive conditions.

Notably, the findings of the present dissertation project do not necessarily hold for other exercises or movement techniques. This includes exercises with a fixed movement cadence controlled by a metronome, which has commonly been considered an essential factor for standardization in previous research on strength-endurance modeling (Arakelian et al., 2017; Dinyer, Byrd, Vesotsky, Succi, & Bergstrom, 2019; R. H. Morton et al., 2014). However, in the author's opinion, this standardization measure does not reflect typical resistance training practices.

3.3.3 Load spectrum

All experiments were completed at loads ranging from 70% to 100% 1-RM. This spectrum was selected for two main reasons. First, it covers most of the load range recommended in the American College of Sports Medicine (ACSM) position stand to promote muscle hypertrophy and strength adaptations (Ratamess et al., 2009). Second, it was assumed that including lower relative loads in the single-visit protocol would have induced greater fatigue levels, resulting in more biased parameter estimates. This assumption was based on an unpublished pilot study including nine resistance-trained men that used the same single-visit protocol of publication #1, with an additional 60% 1-RM load at the end of it.

The findings of the present thesis on model validity and the bias inherent to the single-visit protocol do not necessarily apply to other load ranges. It may be assumed that when considering a full spectrum of external loads between 0% and 100% 1-RM, the relationship will likely continue a curvilinear trend, as proposed by investigations including exceptionally low loads around 20% to 30% 1-RM (Arakelian et al., 2017; Desgorces et al., 2010). However, it cannot be ruled out that functions other than Ex2 and Rec provide higher predictive accuracy and more robust parameter estimates across larger load spectrums. In addition, Ex2 and Rec are characterized by a fixed asymptote at a relative load of 0% 1-RM, which may be considered an inadequate model restriction at the lower-load end. On the other hand, Ex3 and Crt express the load asymptote as a parameter in the model function (i.e., *c* in Ex3; and *CL* in Crt). Presuming that these parameters are not truncated during model fitting, this renders the lower-load end non-restrictive for Ex3 and Crt and allows for an actual intercept with the RTF axis. Nevertheless, the practical relevance for model accuracy at the exceptionally low load range could be questioned, especially considering that this range may be prone to a substantially lower absolute test-retest agreement in RTF completed due to a longer set duration.

3.3.4 Bias in the single-visit protocol

As shown in publication #3, applying a single-visit protocol to assess RTF at 90%, 80%, and 70% 1-RM in the bench press likely biases the result of the 70% 1-RM trial. Although the tested variant of the bench press differs slightly from that used in publications #1 and #2, the main findings of publication #3 challenge the validity of the results in the two other studies. However, as evidenced in the replication analysis performed in publication #3, applying a multi-visit protocol yielded comparable results to publication #1. Therefore, the potential bias observed in the data has not substantially affected the ranking of model performance.

The inherent bias of the single-visit protocol might have also influenced the findings from Publication #2. Presuming that biological noise is proportional to performance at a robust ratio, the reported statistics for absolute test-retest consistency of RTF completed at 70% 1-RM may not have represented biological variability under a proper rested condition state. However, whether this potential bias substantially affected test-retest agreement in the investigated load range may be questioned. As shown in publication #2, the within-subject coefficient of variation of RTF at 80% and 70% 1-RM was estimated at about 10% (Mitter, Csapo, et al., 2022). Following the results of publication #3, it may be suggested that the single-visit protocol yielded an average negative bias of about two repetitions in the 70% 1-

RM trial (Mitter, Raidl, et al., 2022). Therefore, the estimated standard error of measurement at 70% 1-RM might only have been affected by a magnitude of about 0.2 repetitions. Similarly, the results reported on the robustness of model parameters may be predominantly attributed to the mathematical properties of the investigated functions rather than small deviations in observed biological noise. To identify whether conclusions made in publication #2 are predominantly ascribed to the use of a single-visit protocol in the experimental design, further research is needed.

3.4 Outlook

Research on the individual strength-endurance relationship is still in its early stages, leaving numerous questions to be addressed in future investigations. The present section will discuss two main objectives that are of interest in terms of practical relevance.

3.4.1 Replication

Future studies should evaluate the performance and robustness of different model functions in multiple exercises to identify whether the strength-endurance relationship can be universally modeled with a single function. This includes isolated exercises and other popular compound exercises, such as the back squat and the deadlift. Such investigations may also consider deploying additional curvilinear functions. Recently, it has been suggested that omitting the intercept and forcing the function to pass through the 1-RM may be a possible method to simplify functions which express an intercept parameter (Jovanovic, 2022). When expressing load relative to the 1-RM, this can be achieved by setting RTF to 1, load to 100, solving the resulting equation for the intercept parameter, and plugging it into the original bivariate function. The computational details of this process are illustrated below using the 2-parameters exponential model (Eq. 15) as an example:

$$load = a\, e^{b\, RTF} \qquad | \; load = 100; RTF = 1$$

$$100 = a\, e^{b} \qquad | \div e^{b}$$

$$\frac{100}{e^{b}} = a \qquad | \; plug\ in\ Eq. 15$$

$$load = \frac{100}{e^{b}}\, e^{b\, RTF} \qquad | \; apply\ division\ rule$$

$$load = 100\, e^{b\, RTF - b} \qquad | \; extract\ b$$

$$load = 100\, e^{b\, (RTF-1)} \qquad (35)$$

As portrayed in eq. 35 and illustrated in Figure 12, the simplified model features only a single parameter *b* and will pass through the 1-RM load irrespective of the parameter value. It should be noted that the model assumes prior knowledge about the 1-RM load, expressed by the value 100 in eq. 35 (i.e., 100% 1-RM). It further assumes that the information about the 1-RM load is free of error and bias. While the 1-RM test has repeatedly been shown to be reliable (Grgic, Lazinica, et al., 2020), this assumption is somewhat unrealistic, especially when indirect methods are used to predict the 1-RM of compound exercises in well-trained individuals (Mitter, 2018; Mitter, Bauer, & Tschan, 2021; Weakley et al., 2021). Furthermore, the reduced number of model parameters negatively affects model flexibility because it restricts the potential shape the function may take. Future research should investigate whether these restrictive properties of simplified functions substantially affect model validity and robustness.

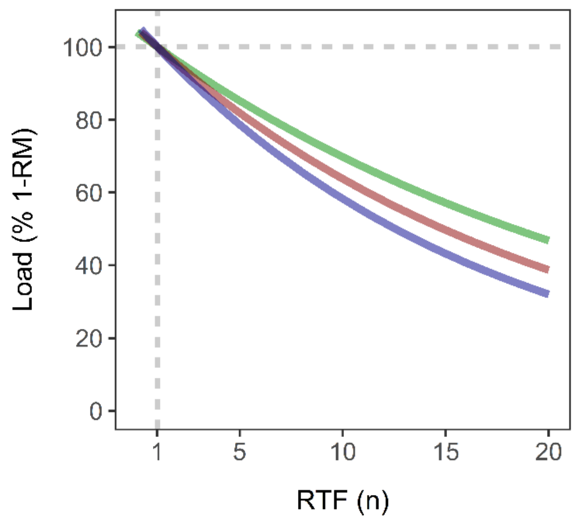

Figure 12. Simplified single-parameter version of the exponential function (eq. 35). The displayed models are based on the 2-parameter exponential model. The intercept parameter was omitted, and the function was forced to pass through the 1-RM load (i.e., 100% 1-RM). The solid lines display the model function, assuming curvature parameters *b* equal to -0.04 (top), -0.05 (middle), and -0,06 (bottom). The dashed grey lines mark the 1-RM load. 1-RM, one-repetition maximum; RTF, repetitions performed to momentary failure.

3.4.2 Inter-set fatigue

It is essential to acknowledge that strength-endurance profiles are conceptually designed to portray a cross-sectional state of an individual's performance limit. Thus, they assume a relationship between load and RTF under rested conditions. However, over the course of multiple consecutive sets, fatigue may arise and potentially alter this relationship. To provide accurate predictions across subsequent sets, then, inter-set fatigue must be accounted for within models. Therefore, future research should investigate the effects of inter-set fatigue on the individual strength-endurance relationship. For example, it could be investigated whether the strength-endurance relationship experiences a constant decay (i.e., a parallel shift) due to fatigue by applying a standardized fatiguing set prior to the RTF test used for profile computation. It might also be interesting to investigate the possibility of modeling inter-set fatigue as a function of the applied load, the number of repetitions, and rest duration. However, this type of exploratory research would likely require a cross-over study design with a large number of participants and multiple consecutive sessions for each participant to account for a variety of different fatiguing conditions. Therefore, it may be valuable first to consider further research on single-visit protocols to identify a rest interval at which strength endurance has approximately recovered for different loads.

4 Abbreviations

1-RM	One-repetition maximum
ADP	Adenosine diphosphate
AMP	Adenosine monophosphate
ATP	Adenosine triphosphate
BM	Body mass
Ca^{2+}	Calcium
Cl^{-}	Chloride
Cr	Creatine
e.g.	Example given
F	Force
FI	Fatigue index
FTI	Force-Time Integral
H^{+}	Hydrogen
HFF	High-frequency fatigue
HDI	Highest density interval
i.e.	In explanation
IMP	Inosine monophosphate
K^{+}	Potassium

La	Lactic acid
LFF	Low-frequency fatigue
LME	Local muscular endurance
$load_a$	Applied load
$load_{max}$	Predicted maximum load
MCV	Maximum voluntary contraction
MEP	Motor-evoked potential
MLSS	Maximum lactate steady state
MNS	Motor nerve stimulation
MV	Multi-visit (protocol)
n_a	Applied number of repetitions
n_{max}	Predicted maximum number of repetitions
n-RM	n-repetition maximum
Na^+	Sodium
NH_3	Ammonia
P	Power
PA	Pennation angle
PCr	Phosphocreatine
P_i	Inorganic phosphate
RCP	Respiratory compensation point
RE	Relative effort
REv	Vectorized relative effort
RI_{SR}	Relative intensity of set-repetition best
RIR	Repetitions in reserve
ROS	Reactive oxygen species
RTF	Number of repetitions to momentary failure
SE	Strength endurance
SEM	Standard error of measurement
SV	Single-visit (protocol)
syn	Synonymously
t_{lim}	Time to exhaustion
TMS	Transcranial magnetic stimulation
VA	Voluntary activation
W	Work

5 References

Adams, G. M., & Beam, W. C. (2014). *Exercise physiology laboratory manual* (Seventh edition). McGraw-Hill.

Alcazar, J., Cornejo-Daza, P. J., Sánchez-Valdepeñas, J., Alegre, L. M., & Pareja-Blanco, F. (2021). Dose-Response Relationship Between Velocity Loss During Resistance Training and Changes in the Squat Force-Velocity Relationship. *International Journal of Sports Physiology and Performance*, *16*(12), 1736–1745. https://doi.org/10.1123/ijspp.2020-0692

Allen, D. G., Lamb, G. D., & Westerblad, H. (2008). Skeletal muscle fatigue: Cellular mechanisms. *Physiological Reviews*, *88*(1), 287–332. https://doi.org/10.1152/physrev.00015.2007

Anderson, T., & Kearney, J. T. (1982). Effects of three resistance training programs on muscular strength and absolute and relative endurance. *Research Quarterly for Exercise and Sport*, *53*(1), 1–7. https://doi.org/10.1080/02701367.1982.10605218

Ansdell, P., Brownstein, C. G., Škarabot, J., Hicks, K. M., Howatson, G., Thomas, K., Hunter, S. K., & Goodall, S. (2019). Sex differences in fatigability and recovery relative to the intensity-duration relationship. *The Journal of Physiology*, *597*(23), 5577–5595. https://doi.org/10.1113/jp278699

Arakelian, V. M., Goulart, C. d. L., Mendes, R. G., Caruso, F. C., Baldissera, V., Arena, R., & Borghi-Silva, A. (2018). Cardiorespiratory and metabolic determinants during moderate and high resistance exercise intensities until exhaustion using dynamic leg press: Comparison with critical load. *Brazilian Journal of Medical and Biological Research = Revista Brasileira De Pesquisas Medicas E Biologicas*, *51*(11), e7837. https://doi.org/10.1590/1414-431X20187837

Arakelian, V. M., Goulart, C. d. L., Mendes, R. G., Sousa, N. M. d., Trimer, R., Guizilini, S., Sampaio, L. M. M., Baldissera, V., Arena, R., Reis, M. S., & Borghi-Silva, A. (2019). Physiological responses in different intensities of resistance exercise - Critical load and the effects of aging process. *Journal of Sports Sciences*, *37*(12), 1420–1428. https://doi.org/10.1080/02640414.2018.1561389

Arakelian, V. M., Mendes, R. G., Trimer, R., Rossi Caruso, F. C., Sousa, N. M. d., Borges, V. C., do Valle Gomes Gatto, C., Baldissera, V., Arena, R., & Borghi-Silva, A. (2017). Critical load: A novel approach to determining a sustainable intensity during resistance exercise. *The Journal of Sports Medicine and Physical Fitness*, *57*(5), 556–564. https://doi.org/10.23736/S0022-4707.16.06169-7

Arazi, H., & Asadi, A. (2011). The relationship between the selected percentages of one repetition maximum and the number of repetitions in trained and untrained males. *Electronic Physician*, *9*(1), 25–33.

Armes, C., Standish-Hunt, H., Androulakis-Korakakis, P., Michalopoulos, N., Georgieva, T., Hammond, A., Fisher, J. P., Gentil, P., Giessing, J., & Steele, J. (2020). "Just One More Rep!" - Ability to Predict Proximity to Task Failure in Resistance Trained Persons. *Frontiers in Psychology*, *11*, 565416. https://doi.org/10.3389/fpsyg.2020.565416

Babyak, M. A. (2004). What You See May Not Be What You Get: A Brief, Nontechnical Introduction to Overfitting in Regression-Type Models. *Psychosomatic Medicine*, *66*(3), 411–421. https://doi.org/10.1097/00006842-200405000-00021

Baker, A. J., Kostov, K. G., Miller, R. G., & Weiner, M. W. (1993). Slow force recovery after long-duration exercise: Metabolic and activation factors in muscle fatigue. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *74*(5), 2294–2300. https://doi.org/10.1152/jappl.1993.74.5.2294

Bandy, W. D., Lovelace-Chandler, V., & McKitrick-Bandy, B. (1990). Adaptation of skeletal muscle to resistance training. *The Journal of Orthopaedic and Sports Physical Therapy*, *12*(6), 248–255. https://doi.org/10.2519/jospt.1990.12.6.248

Barnes, W. S. (1980). The relationship between maximum isometric strength and intramuscular circulatory occlusion. *Ergonomics*, *23*(4), 351–357. https://doi.org/10.1080/00140138008924748

Barry, B. K., & Enoka, R. M. (2007). The neurobiology of muscle fatigue: 15 years later. *Integrative and Comparative Biology*, *47*(4), 465–473. https://doi.org/10.1093/icb/icm047

Benavides-Ubric, A., Díez-Fernández, D. M., Rodríguez-Pérez, M. A., Ortega-Becerra, M., & Pareja-Blanco, F. (2020). Analysis of the Load-Velocity Relationship in Deadlift Exercise. *Journal of Sports Science & Medicine*, *19*(3), 452–459.

Berger, R. A. (1961). Determination of resistance load for 1-RM and 10-RM. *Journal of the Association for Physical and Mental Rehabilitation*, *51*, 100-110.

Berger, R. A. (1970). Relationship between Dynamic Strength and Dynamic Endurance. *Research Quarterly. American Association for Health, Physical Education and Recreation*, *41*(1), 115–116. https://doi.org/10.1080/10671188.1970.10614955

Bergstrom, H. C., Dinyer, T. K., Succi, P. J., Voskuil, C. C., & Housh, T. J. (2021). Applications of the Critical Power Model to Dynamic Constant External Resistance Exercise: A Brief Review of the Critical Load Test. *Sports (Basel, Switzerland)*, *9*(2), 15. https://doi.org/10.3390/sports9020015

Bigland-Ritchie, B., Cafarelli, E., & Vøllestad, N. K. (1986). Fatigue of submaximal static contractions. *Acta Physiologica Scandinavica. Supplementum*, *556*, 137–148.

Bigland-Ritchie, B., Furbush, F., & Woods, J. J. (1986). Fatigue of intermittent submaximal voluntary contractions: Central and peripheral factors. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *61*(2), 421–429. https://doi.org/10.1152/jappl.1986.61.2.421

Bloomer, R. J., Falvo, M. J., Fry, A. C., Schilling, B. K., Smith, W. A., & Moore, C. A. (2006). Oxidative stress response in trained men following repeated squats or sprints. *Medicine and Science in Sports and Exercise*, *38*(8), 1436–1442. https://doi.org/10.1249/01.mss.0000227408.91474.77

Brancaccio, P., Limongelli, F. M., D'Aponte, A., Narici, M., & Maffulli, N. (2008). Changes in skeletal muscle architecture following a cycloergometer test to exhaustion in athletes. *Journal of Science and Medicine in Sport*, *11*(6), 538–541. https://doi.org/10.1016/j.jsams.2007.05.011

Brechue, W. F., & Mayhew, J. L. (2009). Upper-body work capacity and 1RM prediction are unaltered by increasing muscular strength in college football players. *Journal of Strength and Conditioning Research*, *23*(9), 2477–2486. https://doi.org/10.1519/JSC.0b013e3181b1ae5f

Briscoe, E., & Feldman, J. (2011). Conceptual complexity and the bias/variance tradeoff. *Cognition*, *118*(1), 2–16. https://doi.org/10.1016/j.cognition.2010.10.004

Brooks, G. A., Fahey, T. D., & Baldwin, K. M. (2005). *Exercise physiology: Human bioenergetics and its applications* (Fouth edition). McGraw Hill.

Brown, H. L. (1992). *Lifetime fitness* (3rd ed.). Gorsuch Scarisbrick.

Brzycki, M. (1993). Strength Testing - Predicting a One-Rep Max from Reps-to-Fatigue. *Journal of Physical Education, Recreation & Dance*, *64*(1), 88–90. https://doi.org/10.1080/07303084.1993.10606684

Buitrago, S., Wirtz, N., Yue, Z., Kleinöder, H., & Mester, J. (2012). Effects of load and training modes on physiological and metabolic responses in resistance exercise. *European Journal of Applied Physiology*, *112*(7), 2739–2748. https://doi.org/10.1007/s00421-011-2249-9

Cairns, S. P., Knicker, A. J., Thompson, M. W., & Sjøgaard, G. (2005). Evaluation of models used to study neuromuscular fatigue. *Exercise and Sport Sciences Reviews*, *33*(1), 9–16.

Carneiro, M., Oliveira Júnior, G. N. de, Sousa, J. de, Souza, M. V. C., & Orsatti, F. L. (2020). Cluster training sets is an important stimulus for promoting gains in muscle power regardless of resistance training program design in older women. *Science & Sports*, *35*(4), 239.e1-239.e8. https://doi.org/10.1016/j.scispo.2019.08.003

Carroll, K. M., Bazyler, C. D., Bernards, J. R., Taber, C. B., Stuart, C. A., DeWeese, B. H., Sato, K., & Stone, M. H. (2019). Skeletal Muscle Fiber Adaptations Following Resistance Training Using Repetition Maximums or Relative Intensity. *Sports (Basel, Switzerland)*, *7*(7). https://doi.org/10.3390/sports7070169

Carroll, K. M., Bernards, J. R., Bazyler, C. D., Taber, C. B., Stuart, C. A., DeWeese, B. H., Sato, K., & Stone, M. H. (2019). Divergent Performance Outcomes Following Resistance Training Using Repetition Maximums or Relative Intensity. *International Journal of Sports Physiology and Performance*(14), Article 1, 46–54. https://doi.org/10.1123/ijspp.2018-0045

Cavarretta, D. J., Hall, E. E., & Bixby, W. R. (2019a). The acute effects of resistance exercise on affect, anxiety, and mood – practical implications for designing resistance training programs. *International Review of Sport and Exercise Psychology*, *12*(1), 295–324. https://doi.org/10.1080/1750984X.2018.1474941

Cavarretta, D. J., Hall, E. E., & Bixby, W. R. (2019b). Affective Responses From Different Modalities of Resistance Exercise: Timing Matters! *Frontiers in Sports and Active Living*, *1*, 5. https://doi.org/10.3389/fspor.2019.00005

Cavarretta, D. J., Hall, E. E., & Bixby, W. R. (2022). The Effects of Increasing Training Load on Affect and Perceived Exertion. *Journal of Strength and Conditioning Research*, *36*(1), 16–21. https://doi.org/10.1519/JSC.0000000000003393

Chaabene, H., Negra, Y., Bouguezzi, R., Mkaouer, B., Franchini, E., Julio, U., & Hachana, Y. (2017). Physical and Physiological Attributes of Wrestlers: An Update. *Journal of Strength and Conditioning Research*, *31*(5), 1411–1442. https://doi.org/10.1519/JSC.0000000000001738

Chapman, P. P., Whitehead, J. R., & Binkert, R. H. (1998). The 225–1b Reps-to-Fatigue Test as a Submaximal Estimate of 1-RM Bench Press Performance in College Football Players. *Journal of Strength and Conditioning Research*, *12*(4), 258–261.

Clarke, D. C., & Skiba, P. F. (2013). Rationale and resources for teaching the mathematical modeling of athletic training and performance. *Advances in Physiology Education*, *37*(2), 134–152. https://doi.org/10.1152/advan.00078.2011

Costa, R. R. G., & Ribeiro Neto, F. (2018). Cross-validity of one maximum repetition predictive equation for men with spinal cord injury. *The Journal of Spinal Cord Medicine*, 1–6. https://doi.org/10.1080/10790268.2018.1547861

Courel-Ibáñez, J., Martínez-Cava, A., Morán-Navarro, R., Escribano-Peñas, P., Chavarren-Cabrero, J., González-Badillo, J. J., & Pallarés, J. G. (2019). Reproducibility and Repeatability of Five Different Technologies for Bar Velocity Measurement in Resistance Training. *Annals of Biomedical Engineering*, *47*(7), 1523–1538. https://doi.org/10.1007/s10439-019-02265-6

Cronin, J. B., & Henderson, M. E. (2004). Maximal strength and power assessment in novice weight trainers. *Journal of Strength and Conditioning Research*, *18*(1), 48–52. https://doi.org/10.1519/00124278-200402000-00006

Csapo, R., Alegre, L. M., & Baron, R. (2011). Time kinetics of acute changes in muscle architecture in response to resistance exercise. *Journal of Science and Medicine in Sport*, *14*(3), 270–274. https://doi.org/10.1016/j.jsams.2011.02.003

Cummings, B., & Finn, K. J. (1998). Estimation of a One Repetition Maximum Bench Press for Untrained Women. *Journal of Strength and Conditioning Research*, *12*(4), 262. https://doi.org/10.1519/1533-4287(1998)012<0262:EOAORM>2.3.CO;2

Davis, J. M., & Bailey, S. P. (1997). Possible mechanisms of central nervous system fatigue during exercise. *Medicine and Science in Sports and Exercise*, *29*(1), 45–57. https://doi.org/10.1097/00005768-199701000-00008

Debold, E. P., Dave, H., & Fitts, R. H. (2004). Fiber type and temperature dependence of inorganic phosphate: Implications for fatigue. *American Journal of Physiology. Cell Physiology*, *287*(3), C673-81. https://doi.org/10.1152/ajpcell.00044.2004

Deminice, R., Sicchieri, T., Payão, P. O., & Jordão, A. A. (2010). Blood and salivary oxidative stress biomarkers following an acute session of resistance exercise in humans. *International Journal of Sports Medicine*, *31*(9), 599–603. https://doi.org/10.1055/s-0030-1255107

Deschenes, M. R., & Kraemer, W. J. (2002). Performance and physiologic adaptations to resistance training. *American Journal of Physical Medicine & Rehabilitation*, *81*(11 Suppl), S3-16. https://doi.org/10.1097/00002060-200211001-00003

Desgorces, F. D., Berthelot, G., Dietrich, G., & Testa, M. S. A. (2010). Local muscular endurance and prediction of 1 repetition maximum for bench in 4 athletic populations. *Journal of Strength and Conditioning Research*, *24*(2), 394–400. https://doi.org/10.1519/JSC.0b013e3181c7c72d

DeWeese, B. H., Hornsby, G., Stone, M. E., & Stone, M. H. (2015). The training process: Planning for strength–power training in track and field. Part 2: Practical and applied aspects. *Journal of Sport and Health Science*, *4*(4), 318–324. https://doi.org/10.1016/j.jshs.2015.07.002

Dinyer, T. K., Byrd, M. T., Succi, P. J., & Bergstrom, H. C. (2020). The Time Course of Changes in Neuromuscular Responses During the Performance of Leg Extension Repetitions to Failure Below and Above Critical Resistance in Women. *Journal of Strength and Conditioning Research.* Advance online publication. https://doi.org/10.1519/JSC.0000000000003529

Dinyer, T. K., Byrd, M. T., Succi, P. J., Clasey, J. L., & Bergstrom, H. C. (2020). Contributions of Maximal Strength and Body Composition Characteristics to Resistance Exercise Performance at the Critical Load. *Journal of Exercise Physiology Online*, *23*(3), 25–37.

Dinyer, T. K., Byrd, M. T., Vesotsky, A. N., Succi, P. J., & Bergstrom, H. C. (2019). Applying the Critical Power Model to a Full-Body Resistance-Training Movement. *International Journal of Sports Physiology and Performance*, *14*(10), 1364–1370. https://doi.org/10.1123/ijspp.2018-0981

Dinyer, T. K., Byrd, M. T., Vesotsky, A. N., Succi, P. J., & Bergstrom, H. C. (2020). Linear and Nonlinear Modeling of Critical Load. *Journal of Exercise Physiology Online*, *23*(5), 1–13.

Dinyer, T. K., Byrd, M. T., Vesotsky, A. N., Succi, P. J., Clasey, J. L., & Bergstrom, H. C. (2019). The Sensitivity of the Critical Resistance Model to Detect Sex-Related Differences in Fatigue During Submaximal Muscular Contractions. *Journal of Science in Sport and Exercise*, *1*(2), 151–158. https://doi.org/10.1007/s42978-019-0025-4

DiStasio, T. J. (2014). *Validation of the Brzycki and Epley Equations for the 1 Repetition Maximum Back Squat Test in Division I College Football Players* [Master's Thesis]. Southern Illinois University Carbondale, Carbondale.

Dohoney, P., Chromiak, J. A., Lemire, D., Abadie, B. R., & Kovacs, C. (2002). Prediction of One Repetition Maximum (1-RM) Strength from a 4-6 RM and a 7-10 RM Submaximal Strength Test in Healthy Young Adult Males. *Journal of Exercise Physiology Online*, *5*(3), 54–59.

Douris, P. C., White, B. P., Cullen, R. R., Keltz, W. E., Meli, J., Mondiello, D. M., & Wenger, D. (2006). The relationship between maximal repetition performance and muscle fiber type as estimated by noninvasive technique in the quadriceps of untrained women. *Journal of Strength and Conditioning Research*, *20*(3), 699–703. https://doi.org/10.1519/17204.1

Edwards, R. H., Hill, D. K., Jones, D. A., & Merton, P. A. (1977). Fatigue of long duration in human skeletal muscle after exercise. *The Journal of Physiology*, *272*(3), 769–778. https://doi.org/10.1113/jphysiol.1977.sp012072

Emanuel, A., Rozen Smukas, I. I., & Halperin, I. (2020). An analysis of the perceived causes leading to task-failure in resistance-exercises. *PeerJ*, *8*, e9611. https://doi.org/10.7717/peerj.9611

Enoka, R. M., & Duchateau, J. (2008). Muscle fatigue: What, why and how it influences muscle function. *The Journal of Physiology*, *586*(1), 11–23. https://doi.org/10.1113/jphysiol.2007.139477

Epley, B. (1985). *Poundage Chart: Boyd Epley Workout*. Body Enterprises.

Fabiato, A., & Fabiato, F. (1978). Effects of pH on the myofilaments and the sarcoplasmic reticulum of skinned cells from cardiace and skeletal muscles. *The Journal of Physiology*, *276*, 233–255. https://doi.org/10.1113/jphysiol.1978.sp012231

Farrow, J., Steele, J., Behm, D. G., Skivington, M., & Fisher, J. P. (2021). Lighter-Load Exercise Produces Greater Acute- and Prolonged-Fatigue in Exercised and Non-Exercised Limbs. *Research Quarterly for Exercise and Sport*, *92*(3), 369–379. https://doi.org/10.1080/02701367.2020.1734521

Felipo, V., & Butterworth, R. F. (2002). Neurobiology of ammonia. *Progress in Neurobiology*, *67*(4), 259–279. https://doi.org/10.1016/s0301-0082(02)00019-9

Finsterer, J. (2012). Biomarkers of peripheral muscle fatigue during exercise. *BMC Musculoskeletal Disorders*, *13*, 218. https://doi.org/10.1186/1471-2474-13-218

Fisher, J. P., & Steele, J. (2017). Heavier and lighter load resistance training to momentary failure produce similar increases in strength with differing degrees of discomfort. *Muscle & Nerve*, *56*(4), 797–803. https://doi.org/10.1002/mus.25537

Fisher, J. P., Steele, J., Androulakis-Korakakis, P., Smith, D., Gentil, P., & Giessing, J. (2020). The strength-endurance continuum revisited:a critical commentary of the recommendation ofdifferent loading ranges for different muscular adaptations. *Journal of Trainology*, *9*(1), 1–8. https://doi.org/10.17338/trainology.9.1_1

Fisher, J. P., Steele, J., & Smith, D. (2022). Intensity of effort and momentary failure in resistance training: Are we asking a binary question for a continuous variable? *Journal of Sport and Health Science.* Advance online publication. https://doi.org/10.1016/j.jshs.2022.03.002

Fisher, J. P., Stuart, C., Steele, J., Gentil, P., & Giessing, J. (2018). Heavier- and lighter-load isolated lumbar extension resistance training produce similar strength increases, but different perceptual responses, in healthy males and females. *PeerJ*, *6*, e6001. https://doi.org/10.7717/peerj.6001

Fitts, R. H. (1994). Cellular mechanisms of muscle fatigue. *Physiological Reviews*, *74*(1), 49–94. https://doi.org/10.1152/physrev.1994.74.1.49

Fitts, R. H. (2008). The cross-bridge cycle and skeletal muscle fatigue. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *104*(2), 551–558. https://doi.org/10.1152/japplphysiol.01200.2007

Fonseca, F. S., Costa, B. D. d. V., Ferreira, M. E. C., Paes, S., Lima-Junior, D. de, Kassiano, W., Cyrino, E. S., Gantois, P., & Fortes, L. S. (2020). Acute effects of equated volume-load resistance training leading to muscular failure versus non-failure on neuromuscular performance. *Journal of Exercise Science and Fitness*, *18*(2), 94–100. https://doi.org/10.1016/j.jesf.2020.01.004

Froyd, C., Beltrami, F. G., & Noakes, T. D. (2018). Neuromuscular Fatigue at Task Failure and During Immediate Recovery after Isometric Knee Extension Trials. *Sports (Basel, Switzerland)*, *6*(4). https://doi.org/10.3390/sports6040156

Galán-Rioja, M. Á., González-Mohíno, F., Poole, D. C., & González-Ravé, J. M. (2020). Relative Proximity of Critical Power and Metabolic/Ventilatory Thresholds: Systematic Review and Meta-Analysis. *Sports Medicine (Auckland, N.Z.)*, *50*(10), 1771–1783. https://doi.org/10.1007/s40279-020-01314-8

Gandevia, S. C. (2001). Spinal and supraspinal factors in human muscle fatigue. *Physiological Reviews*, *81*(4), 1725–1789. https://doi.org/10.1152/physrev.2001.81.4.1725

García-Ramos, A., Haff, G. G., Pestaña-Melero, F. L., Pérez-Castilla, A., Rojas, F. J., Balsalobre-Fernández, C., & Jaric, S. (2018). Feasibility of the 2-Point Method for Determining the 1-Repetition Maximum in the Bench Press Exercise. *International Journal of Sports Physiology and Performance*, *13*(4), 474–481. https://doi.org/10.1123/ijspp.2017-0374

García-Ramos, A., Ulloa-Díaz, D., Barboza-González, P., Rodríguez-Perea, Á., Martínez-García, D., Quidel-Catrilelbún, M., Guede-Rojas, F., Cuevas-Aburto, J., Janicijevic, D., & Weakley, J. (2019). Assessment of the load-velocity profile in the free-weight prone bench pull exercise through different velocity variables and regression models. *PloS One*, *14*(2), e0212085. https://doi.org/10.1371/journal.pone.0212085

Gigerenzer, G., & Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, *1*(1), 107–143. https://doi.org/10.1111/j.1756-8765.2008.01006.x

Goldfarb, A. H., Garten, R. S., Chee, P. D. M., Cho, C., Reeves, G. V., Hollander, D. B., Thomas, C., Aboudehen, K. S., Francois, M., & Kraemer, R. R. (2008). Resistance exercise effects on blood glutathione status and plasma protein carbonyls: Influence of partial vascular occlusion. *European Journal of Applied Physiology*, *104*(5), 813–819. https://doi.org/10.1007/s00421-008-0836-1

Gómez-Landero, L. A., & Frías-Menacho, J. M. (2020). Analysis of Morphofunctional Variables Associated with Performance in Crossfit® Competitors. *Journal of Human Kinetics*, *73*, 83–91. https://doi.org/10.2478/hukin-2019-0134

Goodall, S., Thomas, K., Barwood, M., Keane, K., Gonzalez, J. T., St.Clair Gibson, A., & Howatson, G. (2017). Neuromuscular changes and the rapid adaptation following a bout of damaging eccentric exercise. *Acta Physiologica (Oxford, England)*, *220*(4), 486–500. https://doi.org/10.1111/apha.12844

Gorostiaga, E. M., Navarro-Amézqueta, I., Calbet, J. A. L., Hellsten, Y., Cusso, R., Guerrero, M., Granados, C., González-Izal, M., Ibáñez, J., & Izquierdo, M. (2012). Energy metabolism during repeated sets of leg press exercise leading to failure or not. *PloS One*, *7*(7), e40621. https://doi.org/10.1371/journal.pone.0040621

Gorostiaga, E. M., Navarro-Amézqueta, I., Calbet, J. A. L., Sánchez-Medina, L., Cusso, R., Guerrero, M., Granados, C., González-Izal, M., Ibáñez, J., & Izquierdo, M. (2014). Blood ammonia and lactate as markers of muscle metabolites during leg press exercise. *Journal of Strength and Conditioning Research*, *28*(10), 2775–2785. https://doi.org/10.1519/JSC.0000000000000496

Gorostiaga, E. M., Navarro-Amézqueta, I., Cusso, R., Hellsten, Y., Calbet, J. A. L., Guerrero, M., Granados, C., González-Izal, M., Ibáñez, J., & Izquierdo, M. (2010). Anaerobic energy expenditure and mechanical efficiency during exhaustive leg press exercise. *PloS One*, *5*(10), e13486. https://doi.org/10.1371/journal.pone.0013486

Graham, T. E., Bangsbo, J., Gollnick, P. D., Juel, C., & Saltin, B. (1990). Ammonia metabolism during intense dynamic exercise and recovery in humans. *The American Journal of Physiology*, *259*(2 Pt 1), E170-6. https://doi.org/10.1152/ajpendo.1990.259.2.E170

Grant, S., Hynes, V., Whittaker, A., & Aitchison, T. (1996). Anthropometric, strength, endurance and flexibility characteristics of elite and recreational climbers. *Journal of Sports Sciences*, *14*(4), 301–309. https://doi.org/10.1080/02640419608727715

Grgic, J., Lazinica, B., Schoenfeld, B. J., & Pedisic, Z. (2020). Test-Retest Reliability of the One-Repetition Maximum (1RM) Strength Assessment: A Systematic Review. *Sports Medicine - Open*, *6*(1), 31. https://doi.org/10.1186/s40798-020-00260-z

Grgic, J., Scapec, B., Pedisic, Z., & Mikulic, P. (2020). Test-Retest Reliability of Velocity and Power in the Deadlift and Squat Exercises Assessed by the GymAware PowerTool System. *Frontiers in Physiology*, *11*, 561682. https://doi.org/10.3389/fphys.2020.561682

Hackett, D. A., Ghayomzadeh, M., Farrell, S. N., Davies, T. B., & Sabag, A. (2022). Influence of total repetitions per set on local muscular endurance: A systematic review with meta-analysis and meta-regression. *Science & Sports.* Advance online publication. https://doi.org/10.1016/j.scispo.2021.11.002

Haff, G. G., & Triplett, N. T. (Eds.). (2016). *Essentials of strength training and conditioning* (Fourth edition). Human Kinetics.

Hahn, G. J. (1977). The Hazards of Extrapolation in Regression Analysis. *Journal of Quality Technology*, *9*(4), 159–165. https://doi.org/10.1080/00224065.1977.11980791

Halperin, I., Malleron, T., Har-Nir, I., Androulakis-Korakakis, P., Wolf, M., Fisher, J. P., & Steele, J. (2021). Accuracy in Predicting Repetitions to Task Failure in Resistance

Exercise: A Scoping Review and Exploratory Meta-analysis. *Sports Medicine (Auckland, N.Z.).* Advance online publication. https://doi.org/10.1007/s40279-021-01559-x

Hernán, M. A., Hsu, J., & Healy, B. (2019). A Second Chance to Get Causal Inference Right: A Classification of Data Science Tasks. *CHANCE*, *32*(1), 42–49. https://doi.org/10.1080/09332480.2019.1579578

Hernández-Belmonte, A., Courel-Ibáñez, J., Conesa-Ros, E., Martínez-Cava, A., & Pallarés, J. G. (2021). Level of Effort: A Reliable and Practical Alternative to the Velocity-Based Approach for Monitoring Resistance Training. *Journal of Strength and Conditioning Research.* Advance online publication. https://doi.org/10.1519/JSC.0000000000004060

Hetzler, R. K., Schroeder, B. L., Wages, J. J., Stickley, C. D., & Kimura, I. F. (2010). Anthropometry increases 1 repetition maximum predictive ability of NFL-225 test for Division IA college football players. *Journal of Strength and Conditioning Research*, *24*(6), 1429–1439. https://doi.org/10.1519/JSC.0b013e3181d682fa

Hickmott, L. M., Chilibeck, P. D., Shaw, K. A., & Butcher, S. J. (2022). The Effect of Load and Volume Autoregulation on Muscular Strength and Hypertrophy: A Systematic Review and Meta-Analysis. *Sports Medicine - Open*, *8*(1), 9. https://doi.org/10.1186/s40798-021-00404-9

Hoeger, W. W., Hopkins, D. R., Barette, S. L., & Hale, D. F. (1990). Relationship between repetitions and selected percentages of one repetition maximum: A comparison between un-trained and trained males and females. *Journal of Strength and Conditioning Research*, *4*(2), 47–54.

Hokken, R., Laugesen, S., Aagaard, P., Suetta, C., Frandsen, U., Ørtenblad, N., & Nielsen, J. (2021). Subcellular localization- and fibre type-dependent utilization of muscle glycogen during heavy resistance exercise in elite power and Olympic weightlifters. *Acta Physiologica (Oxford, England)*, *231*(2), e13561. https://doi.org/10.1111/apha.13561

Horvat, M., Ramsey, V., Franklin, C., Gavin, C., Palumbo, T., & Glass, L. A. (2003). A method for predicting maximal strength in collegiate women athletes. *Journal of Strength and Conditioning Research*, *17*(2), 324–328.

Hughes, L. J., Banyard, H. G., Dempsey, A. R., & Scott, B. R. (2019). Using a Load-Velocity Relationship to Predict One repetition maximum in Free-Weight Exercise: A Comparison of the Different Methods. *Journal of Strength and Conditioning Research*, *33*(9), 2409–2419. https://doi.org/10.1519/JSC.0000000000002550

Hunter, S. K. (2009). Sex differences and mechanisms of task-specific muscle fatigue. *Exercise and Sport Sciences Reviews*, *37*(3), 113–122. https://doi.org/10.1097/JES.0b013e3181aa63e2

Impellizzeri, F. M., Marcora, S. M., & Coutts, A. J. (2019). Internal and External Training Load: 15 Years On. *International Journal of Sports Physiology and Performance*, *14*(2), 270–273. https://doi.org/10.1123/ijspp.2018-0935

Ismaeel, A., Holmes, M., Papoutsi, E., Panton, L. B., & Koutakis, P. (2019). Resistance Training, Antioxidant Status, and Antioxidant Supplementation. *International Journal of Sport Nutrition and Exercise Metabolism*, *29*(5), 539–547. https://doi.org/10.1123/ijsnem.2018-0339

Iversen, V. M., Norum, M., Schoenfeld, B. J., & Fimland, M. S. (2021). No Time to Lift? Designing Time-Efficient Training Programs for Strength and Hypertrophy: A Narrative Review. *Sports Medicine (Auckland, N.Z.)*, *51*(10), 2079–2095. https://doi.org/10.1007/s40279-021-01490-1

Izquierdo-Gabarren, M., González De Txabarri Expósito, R., García-Pallarés, J., Sánchez-Medina, L., Villarreal, E. S. S. de, & Izquierdo, M. (2010). Concurrent endurance and strength training not to failure optimizes performance gains. *Medicine and Science in Sports and Exercise*, *42*(6), 1191–1199. https://doi.org/10.1249/MSS.0b013e3181c67eec

Jansson, E., Dudley, G. A., Norman, B., & Tesch, P. A. (1987). Atp and IMP in single human muscle fibres after high intensity exercise. *Clinical Physiology (Oxford, England)*, *7*(4), 337–345. https://doi.org/10.1111/j.1475-097x.1987.tb00177.x

Johnson, D., Lynch, J., Nash, K., Cygan, J., & Mayhew, J. L. (2009). Relationship of lat-pull repetitions and pull-ups to maximal lat-pull and pull-up strength in men and women. *Journal of Strength and Conditioning Research*, *23*(3), 1022–1028. https://doi.org/10.1519/JSC.0b013e3181a2d7f5

Jones, D. A. (1996). High-and low-frequency fatigue revisited. *Acta Physiologica Scandinavica*, *156*(3), 265–270. https://doi.org/10.1046/j.1365-201X.1996.192000.x

Jones, D. A., Turner, D. L., McIntyre, D. B., & Di Newham, J. (2009). Energy turnover in relation to slowing of contractile properties during fatiguing contractions of the human anterior tibialis muscle. *The Journal of Physiology*, *587*(Pt 17), 4329–4338. https://doi.org/10.1113/jphysiol.2009.175265

Joseph, M. F., Lillie, K. R., Bergeron, D. J., Cota, K. C., Yoon, J. S., Kraemer, W. J., & Denegar, C. R. (2014). Achilles tendon biomechanics in response to acute intense exercise. *Journal of Strength and Conditioning Research*, *28*(5), 1181–1186. https://doi.org/10.1519/JSC.0000000000000361

Jovanovic, M. (2022, February 23). *Load-Exertion Tables And Their Use For Planning – Part 5*. https://complementarytraining.net/load-exertion-tables-and-their-use-for-planning-part-5/

Julio, U., Panissa, V. L. G., & Franchini, E. (2012). Prediction of one repetition maximum from the maximum number of repetitions with submaximal loads in recreationally strength-trained men. *Science & Sports*, *27*(6), e69-e76. https://doi.org/10.1016/j.scispo.2012.07.003

Kataoka, R., Vasenina, E., Hammert, W. B., Ibrahim, A. H., Dankel, S. J., & Buckner, S. L. (2022). Is there Evidence for the Suggestion that Fatigue Accumulates Following Resistance Exercise? *Sports Medicine (Auckland, N.Z.)*, *52*(1), 25–36. https://doi.org/10.1007/s40279-021-01572-0

Kaur, P., Stoltzfus, J., & Yellapu, V. (2018). Descriptive statistics. *International Journal of Academic Medicine*, *4*(1), 60. https://doi.org/10.4103/IJAM.IJAM_7_18

Kaus, R. J. (2014). *Affect and enjoyment associated with crossfit exercise* [Master's thesis, Bowling Green State University, Ohio]. CrossRef.

Keeton, R. B., & Binder-Macleod, S. A. (2006). Low-Frequency Fatigue. *Physical Therapy*, *86*(8), 1146–1150. https://doi.org/10.1093/ptj/86.8.1146

Kemler, E., Valkenberg, H., & Verhagen, E. (2022). More people more active, but there is a counter site. Novice athletes are at highest risk of injury in a large population-based retrospective cross-sectional study. *BMJ Open Sport & Exercise Medicine*, *8*(1), e001255. https://doi.org/10.1136/bmjsem-2021-001255

Kemmler, W. K., Lauber, D., Wassermann, A., & Mayhew, J. L. (2006). Predicting maximal strength in trained postmenopausal woman. *Journal of Strength and Conditioning Research*, *20*(4), 838–842. https://doi.org/10.1519/R-18905.1

Kent-Braun, J. A. (1999). Central and peripheral contributions to muscle fatigue in humans during sustained maximal effort. *European Journal of Applied Physiology and Occupational Physiology*, *80*(1), 57–63. https://doi.org/10.1007/s004210050558

Keyser, R. E. (2010). Peripheral fatigue: High-energy phosphates and hydrogen ions. *PM & R : The Journal of Injury, Function, and Rehabilitation*, *2*(5), 347–358. https://doi.org/10.1016/j.pmrj.2010.04.009

Korzeniewski, B. (2006). Amp deamination delays muscle acidification during heavy exercise and hypoxia. *The Journal of Biological Chemistry*, *281*(6), 3057–3066. https://doi.org/10.1074/jbc.M510418200

Kramer, J. F., Leger, A., Paterson, D. H., & Morrow, A. (1994). Rowing performance and selected descriptive, field, and laboratory variables. *Canadian Journal of Applied Physiology = Revue Canadienne De Physiologie Appliquee*, *19*(2), 174–184. https://doi.org/10.1139/h94-013

Kravitz, L., Akalan, C., Nowicki, K., & Kinzey, S. J. (2003). Prediction of 1 repetition maximum in high-school power lifters. *Journal of Strength and Conditioning Research*, *17*(1), 167–172.

Kubo, K., Kanehisa, H., Kawakami, Y., & Fukunaga, T. (2001). Influences of repetitive muscle contractions with different modes on tendon elasticity in vivo. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *91*(1), 277–282. https://doi.org/10.1152/jappl.2001.91.1.277

Kuramoto, A. K., & Payne, V. G. (1995). Predicting muscular strength in women: A preliminary study. *Research Quarterly for Exercise and Sport*, *66*(2), 168–172. https://doi.org/10.1080/02701367.1995.10762224

LaChance, P. F., & Hortobagyi, T. (1994). Influence of Cadence on Muscular Performance During Push-up and Pull-up Exercise. *Journal of Strength and Conditioning Research*, *8*(2), 76–79.

Lander, J. (1985). Maximum Based on Reps. *National Strength and Conditioning Association Journal*, *6*, 60–61.

Larsen, S., Kristiansen, E., & van den Tillaar, R. (2021). Effects of subjective and objective autoregulation methods for intensity and volume on enhancing maximal strength during resistance-training interventions: A systematic review. *PeerJ*, *9*, e10663. https://doi.org/10.7717/peerj.10663

Latella, C., Hendy, A. M., Pearce, A. J., VanderWesthuizen, D., & Teo, W.-P. (2016). The Time-Course of Acute Changes in Corticospinal Excitability, Intra-Cortical Inhibition and Facilitation Following a Single-Session Heavy Strength Training of the Biceps Brachii. *Frontiers in Human Neuroscience*, *10*, 607. https://doi.org/10.3389/fnhum.2016.00607

Laurin, J., Pertici, V., Dousset, E., Marqueste, T., & Decherchi, P. (2015). Group III and IV muscle afferents: Role on central motor drive and clinical implications. *Neuroscience*, *290*, 543–551. https://doi.org/10.1016/j.neuroscience.2015.01.065

Lawton, T. W., Cronin, J. B., & McGuigan, M. R. (2011). Strength testing and training of rowers: A review. *Sports Medicine*, *41*(5), 413–432. https://doi.org/10.2165/11588540-000000000-00000

Leitão, L., Dias, M. C. M., Campos, Y., Vieira, J. G., Sant'Ana, L., Telles, L. G., Tavares, C., Mazini, M., Novaes, J., & Vianna, J. M. (2021). Physical and Physiological Predictors of FRAN CrossFit® WOD Athlete's Performance. *International Journal of Environmental Research and Public Health*, *18*(8). https://doi.org/10.3390/ijerph18084070

Lemos, R. R., Epstein, M., & Herzog, W. (2008). Modeling of skeletal muscle: The influence of tendon and aponeuroses compliance on the force-length relationship. *Medical &*

Biological Engineering & Computing, *46*(1), 23–32. https://doi.org/10.1007/s11517-007-0259-x

LeSuer, D. A., McCormick, J. H., Mayhew, J. L., Wasserstein, R. L., & Arnold, M. D. (1997). The Accuracy of Prediction Equations for Estimating 1-RM Performance in the Bench Press, Squat, and Deadlift. *Journal of Strength and Conditioning Research*, *11*(4), 211–213. https://doi.org/10.1519/00124278-199711000-00001

Lindinger, M. I., & Cairns, S. P. (2021). Regulation of muscle potassium: Exercise performance, fatigue and health implications. *European Journal of Applied Physiology*, *121*(3), 721–748. https://doi.org/10.1007/s00421-020-04546-8

Lombardi, P. V. (1989). *Beginning weight training: The safe and effective way*. Brown.

Lorenz, D. S., Reiman, M. P., & Walker, J. C. (2010). Periodization: Current review and suggested implementation for athletic rehabilitation. *Sports Health*, *2*(6), 509–518. https://doi.org/10.1177/1941738110375910

MacDougall, J. D., Ray, S., Sale, D. G., McCartney, N., Lee, P., & Garner, S. (1999). Muscle substrate utilization and lactate production. *Canadian Journal of Applied Physiology = Revue Canadienne De Physiologie Appliquee*, *24*(3), 209–215. https://doi.org/10.1139/h99-017

Macht, J. W., Abel, M. G., Mullineaux, D. R., & Yates, J. W. (2016). Development of 1RM Prediction Equations for Bench Press in Moderately Trained Men. *Journal of Strength and Conditioning Research*, *30*(10), 2901–2906. https://doi.org/10.1519/JSC.0000000000001385

MacInnis, M. J., & Gibala, M. J. (2017). Physiological adaptations to interval training and the role of exercise intensity. *The Journal of Physiology*, *595*(9), 2915–2930. https://doi.org/10.1113/JP273196

MacIntosh, B. R., & Rassier, D. E. (2002). What is fatigue? *Canadian Journal of Applied Physiology = Revue Canadienne De Physiologie Appliquee*, *27*(1), 42–55. https://doi.org/10.1139/h02-003

Maganaris, C. N., Baltzopoulos, V., & Sargeant, A. J. (2002). Repeated contractions alter the geometry of human skeletal muscle. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *93*(6), 2089–2094. https://doi.org/10.1152/japplphysiol.00604.2002

Mann, J. B., Stoner, J. D., & Mayhew, J. L. (2012). Nfl-225 test to predict 1RM bench press in NCAA Division I football players. *Journal of Strength and Conditioning Research*, *26*(10), 2623–2631. https://doi.org/10.1519/JSC.0b013e31826791ef

Martens, R. (1965). *Relationship of phasic and static strength and endurance* [Master's Thesis]. The University of Montana.

Martínez-Cava, A., Hernández-Belmonte, A., Courel-Ibáñez, J., Morán-Navarro, R., González-Badillo, J. J., & Pallarés, J. G. (2020). Reliability of technologies to measure the barbell velocity: Implications for monitoring resistance training. *PloS One*, *15*(6), e0232465. https://doi.org/10.1371/journal.pone.0232465

Martín-Hernández, J., Marín, P. J., Menéndez, H., Loenneke, J. P., Coelho-e-Silva, M. J., García-López, D., & Herrero, A. J. (2013). Changes in muscle architecture induced by low load blood flow restricted training. *Acta Physiologica Hungarica*, *100*(4), 411–418. https://doi.org/10.1556/APhysiol.100.2013.011

Materko, W., & Santos, E. L. (2009). Prediction of one repetition maximum strength (1RM) based on a submaximal strength in adult males. *Isokinetics and Exercise Science*, *17*(4), 189–195. https://doi.org/10.3233/IES-2009-0353

Mayhew, J. L., Ball, T. E., & Bowen, J. C. (1992). Prediction of bench press lifting ability from submaximal repetitions before and after training. *Sports Medicine, Training and Rehabilitation*, *3*(3), 195–201. https://doi.org/10.1080/15438629209511946

Mayhew, J. L., Johnson, B. D., Lamonte, M. J., Lauber, D., & Kemmler, W. K. (2008). Accuracy of prediction equations for determining one repetition maximum bench press in women before and after resistance training. *Journal of Strength and Conditioning Research*, *22*(5), 1570–1577. https://doi.org/10.1519/JSC.0b013e31817b02ad

Mayhew, J. L., Kerksick, C. D., Lentz, D., Ware, J. S., & Mayhew, D. L. (2004). Using Repetitions to Fatigue to Predict One-Repetition Maximum Bench Press in Male High School Athletes. *Pediatric Exercise Science*, *16*(3), 265–276. https://doi.org/10.1123/pes.16.3.265

Mayhew, J. L., Lauber, D., Kemmler, W. K., Ware, J. S., Ball, T. E., Bemben, M. G., Ward, T. E., & Kerksick, C. D. (2002). Repetitions-to-Fatigue to Predict 1-RM Bench Press in Men With Different Levels of Training. *Medicine and Science in Sports and Exercise*, *34*(5), S289. https://doi.org/10.1097/00005768-200205001-01625

Mayhew, J. L., Ware, J. S., Bemben, M. G., Wilt, B., Ward, T. E., Farris, B., Juraszek, J., & Slovak, J. P. (1999). The NFL-225 Test as a Measure of Bench Press Strength in College Football Players. *Journal of Strength and Conditioning Research*, *13*(2), 130–134. https://doi.org/10.1519/00124278-199905000-00006

Mayhew, J. L., Ware, J. S., & Prinster, J. L. (1993). Using Lift Repetitions to Predict Msucular Strength in Adolescent Males. *National Strength and Conditioning Association Journal*, *15*(6), 35–38.

McNair, P. J., Colvin, M., & Reid, D. (2011). Predicting maximal strength of quadriceps from submaximal performance in individuals with knee joint osteoarthritis. *Arthritis Care & Research*, *63*(2), 216–222. https://doi.org/10.1002/acr.20368

Meeusen, R., Watson, P., Hasegawa, H., Roelands, B., & Piacentini, M. F. (2006). Central fatigue: The serotonin hypothesis and beyond. *Sports Medicine*, *36*(10), 881–909. https://doi.org/10.2165/00007256-200636100-00006

Milner-Brown, H. S., Mellenthin, M., & Miller, R. G. (1986). Quantifying human muscle strength, endurance and fatigue. *Archives of Physical Medicine and Rehabilitation*, *67*(8), 530–535. https://doi.org/10.5555/uri:pii:0003999386905460

Miras-Moreno, S., Pérez-Castilla, A., & García-Ramos, A. (2022). Lifting Velocity as a Predictor of the Maximum Number of Repetitions That Can Be Performed to Failure During the Prone Bench Pull Exercise. *International Journal of Sports Physiology and Performance*, 1–9. https://doi.org/10.1123/ijspp.2021-0534

Mitter, B. (2018). *Velocity-based powerlifting* [Master's Thesis]. University of Vienna, Vienna.

Mitter, B. (2022). *Strength-Endurance Profile* (Version 1.0) [Computer software]. https://strength-and-conditioning-toolbox.shinyapps.io/Strength-Endurance_Profile/

Mitter, B., Bauer, P., & Tschan, H. (2021). Predicting the 1-RM from individualized load-velocity and strength-endurance relationships. In F. Dela, J. W. Helge, E. Müller, & E. Tsolakidis (Eds.), *26th Annual Congress of the European College of Sport Science, 8th - 10th September 2021: Book of abstracts* (p. 75). European College of Sport Science.

Mitter, B., Csapo, R., Bauer, P., & Tschan, H. (2022). Reproducibility of strength performance and strength-endurance profiles: A test-retest study. *PloS One*, *17*(5), e0268074. https://doi.org/10.1371/journal.pone.0268074

Mitter, B., Hölbling, D., Bauer, P., Stöckl, M., Baca, A., & Tschan, H. (2021). Concurrent Validity of Field-Based Diagnostic Technology Monitoring Movement Velocity in Powerlifting Exercises. *Journal of Strength and Conditioning Research*, *35*(8), 2170–2178. https://doi.org/10.1519/JSC.0000000000003143

Mitter, B., Raidl, P., Csapo, R., Bauer, P., & Tschan, H. (2022). *Data Collection for Strength-Endurance Profiles: Can Assessments Be Completed within a Single Session?* [Manuscript submitted for publication]. Centre for Sport Science and University Sports, University of Vienna.

Mitter, B., Zhang, L., Bauer, P., Baca, A., & Tschan, H. (2022). Modeling the Relationship between Load and Repetitions to Failure in Resistance Training: A Bayesian Analysis. *European Journal of Sport Science*, 1–26. https://doi.org/10.1080/17461391.2022.2089915

Monod, H., & Scherrer, J. (1965). The Work Capacity of a Synergic Muscular Group. *Ergonomics*, *8*(3), 329–338. https://doi.org/10.1080/00140136508930810

Morales, J., & Sobonya, S. (1996). Use of submaximal repetition tests for predicting 1-RM strength in class athletes. *Journal of Strength and Conditioning Research*, *10*(3), 186–189.

Morán-Navarro, R., Pérez, C. E., Mora-Rodríguez, R., La Cruz-Sánchez, E. de, González-Badillo, J. J., Sánchez-Medina, L., & Pallarés, J. G. (2017). Time course of recovery following resistance training leading or not to failure. *European Journal of Applied Physiology*, *117*(12), 2387–2399. https://doi.org/10.1007/s00421-017-3725-7

Moritani, T., Nagata, A., deVries, H. A., & Muro, M. (1981). Critical power as a measure of physical work capacity and anaerobic threshold. *Ergonomics*, *24*(5), 339–350. https://doi.org/10.1080/00140138108924856

Morton, R. H. (1996). A 3-parameter critical power model. *Ergonomics*, *39*(4), 611–619. https://doi.org/10.1080/00140139608964484

Morton, R. H., Redstone, M. D., & Laing, D. J. (2014). The Critical Power Concept and Bench Press: Modeling 1RM and Repetitions to Failure. *International Journal of Exercise Science*, *7*(2), 152–160.

Morton, R. W., Sonne, M. W., Farias Zuniga, A., Mohammad, I. Y. Z., Jones, A., McGlory, C., Keir, P. J., Potvin, J. R., & Phillips, S. M. (2019). Muscle fibre activation is unaffected by load and repetition duration when resistance exercise is performed to task failure. *The Journal of Physiology*, *597*(17), 4601–4613. https://doi.org/10.1113/JP278056

Moss, A. C., Dinyer, T. K., Abel, M. G., & Bergstrom, H. C. (2021). Methodological Considerations for the Determination of the Critical Load for the Deadlift. *Journal of Strength and Conditioning Research*, *35*(Suppl 1), S31-S37. https://doi.org/10.1519/JSC.0000000000003795

Nickerson, B. S., Williams, T. D., Snarr, R. L., Garza, J. M., & Salinas, G. (2020). Evaluation of Load-Velocity Relationships and Repetitions-to-Failure Equations in the Presence of Male and Female Spotters. *Journal of Strength and Conditioning Research*, *34*(9), 2427–2433. https://doi.org/10.1519/JSC.0000000000003731

Nikolaidis, M. G., Jamurtas, A. Z., Paschalis, V., Fatouros, I. G., Koutedakis, Y., & Kouretas, D. (2008). The effect of muscle-damaging exercise on blood and skeletal muscle oxidative stress: Magnitude and time-course considerations. *Sports Medicine*, *38*(7), 579–606. https://doi.org/10.2165/00007256-200838070-00005

Nybo, L., & Secher, N. H. (2004). Cerebral perturbations provoked by prolonged exercise. *Progress in Neurobiology*, *72*(4), 223–261. https://doi.org/10.1016/j.pneurobio.2004.03.005

Obst, S. J., Barrett, R. S., & Newsham-West, R. (2013). Immediate effect of exercise on achilles tendon properties: Systematic review. *Medicine and Science in Sports and Exercise*, *45*(8), 1534–1544. https://doi.org/10.1249/MSS.0b013e318289d821

O'Connor, R., Simmons, J., & O'Shea, P. (1989). *Weight training today*. West.

Orssatto, L. B. R., Diefenthaeler, F., Vargas, M., Rossato, M., & La Freitas, C. d. R. (2020). Dissimilar perceptual response between trained women and men in resistance training to concentric failure: A quasi-experimental study. *Journal of Bodywork and Movement Therapies*, *24*(4), 527–535. https://doi.org/10.1016/j.jbmt.2020.06.030

Panissa, V. L. G., Azevedo, N. R. M., Julio, U., Andreato, L. V., Pinto E Silva, C. M., Hardt, F., & Franchini, E. (2013). Maximum number of repetitions, total weight lifted and neuromuscular fatigue in individuals with different training backgrounds. *Biology of Sport*, *30*(2), 131–136. https://doi.org/10.5604/20831862.1044458

Pareja-Blanco, F., Alcazar, J., Sánchez-Valdepeñas, J., Cornejo-Daza, P. J., Piqueras-Sanchiz, F., Mora-Vela, R., Sánchez-Moreno, M., Bachero-Mena, B., Ortega-Becerra, M., & Alegre, L. M. (2020). Velocity Loss as a Critical Variable Determining the Adaptations to Strength Training. *Medicine and Science in Sports and Exercise*, *52*(8), 1752–1762. https://doi.org/10.1249/MSS.0000000000002295

Pareja-Blanco, F., Rodríguez-Rosell, D., Aagaard, P., Sánchez-Medina, L., Ribas-Serna, J., Mora-Custodio, R., Otero-Esquina, C., Yáñez-García, J. M [Juan Manuel], & González-Badillo, J. J. (2020). Time Course of Recovery From Resistance Exercise With Different Set Configurations. *Journal of Strength and Conditioning Research*, *34*(10), 2867–2876. https://doi.org/10.1519/JSC.0000000000002756

Pareja-Blanco, F., Rodríguez-Rosell, D., Sánchez-Medina, L., Sanchis-Moysi, J., Dorado, C., Mora-Custodio, R., Yáñez-García, J. M [J. M.], Morales-Alamo, D., Pérez-Suárez, I., Calbet, J. A. L., & González-Badillo, J. J. (2017). Effects of velocity loss during resistance training on athletic performance, strength gains and muscle adaptations. *Scandinavian Journal of Medicine & Science in Sports*, *27*(7), 724–735. https://doi.org/10.1111/sms.12678

Pareja-Blanco, F., Villalba-Fernández, A., Cornejo-Daza, P. J., Sánchez-Valdepeñas, J., & González-Badillo, J. J. (2019). Time Course of Recovery Following Resistance Exercise with Different Loading Magnitudes and Velocity Loss in the Set. *Sports (Basel, Switzerland)*, *7*(3). https://doi.org/10.3390/sports7030059

Párraga-Montilla, J. A., García-Ramos, A., Castaño-Zambudio, A., Capelo-Ramírez, F., González-Hernández, J. M., Cordero-Rodríguez, Y., & Jiménez-Reyes, P. (2020). Acute and Delayed Effects of a Resistance Training Session Leading to Muscular Failure on Mechanical, Metabolic, and Perceptual Responses. *Journal of Strength and Conditioning Research*, *34*(8), 2220–2226. https://doi.org/10.1519/JSC.0000000000002712

Pascoe, D. D., Costill, D. L., Fink, W. J., Robergs, R. A., & Zachwieja, J. J. (1993). Glycogen resynthesis in skeletal muscle following resistive exercise. *Medicine and Science in Sports and Exercise*, *25*(3), 349–354.

Pearson, S. J., & Onambele, G. N. L. (2005). Acute changes in knee-extensors torque, fiber pennation, and tendon characteristics. *Chronobiology International*, *22*(6), 1013–1027. https://doi.org/10.1080/07420520500397900

Pelland, J. C., Robinson, Z. P., Remmert, J. F., Cerminaro, R. M., Benitez, B., John, T. A., Helms, E. R., & Zourdos, M. C. (2022). Methods for Controlling and Reporting Resistance Training Proximity to Failure: Current Issues and Future Directions. *Sports Medicine (Auckland, N.Z.).* Advance online publication. https://doi.org/10.1007/s40279-022-01667-2

Pérez-Castilla, A., Jukic, I., Janicijevic, D., Akyildiz, Z., Senturk, D., & García-Ramos, A. (2022). Load-Velocity Relationship Variables to Assess the Maximal Neuromuscular Capacities During the Back-Squat Exercise. *Sports Health*, 19417381211064603. https://doi.org/10.1177/19417381211064603

Pettitt, R. W. (2016). Applying the Critical Speed Concept to Racing Strategy and Interval Training Prescription. *International Journal of Sports Physiology and Performance*, *11*(7), 842–847. https://doi.org/10.1123/ijspp.2016-0001

Philippou, A., Maridaki, M., Bogdanis, G., Halapas, A., & Koutsilieris, M. (2009). Changes in the mechanical properties of human quadriceps muscle after eccentric exercise. *In Vivo (Athens, Greece)*, *23*(5), 859–865.

Piqueras-Sanchiz, F., Cornejo-Daza, P. J., Sánchez-Valdepeñas, J., Bachero-Mena, B., Sánchez-Moreno, M., Martín-Rodríguez, S., García-García, Ó., & Pareja-Blanco, F. (2021). Acute Mechanical, Neuromuscular, and Metabolic Responses to Different Set Configurations in Resistance Training. *Journal of Strength and Conditioning Research.* Advance online publication. https://doi.org/10.1519/JSC.0000000000004068

Place, N., & Millet, G. Y. (2020). Quantification of Neuromuscular Fatigue: What Do We Do Wrong and Why? *Sports Medicine (Auckland, N.Z.)*, *50*(3), 439–447. https://doi.org/10.1007/s40279-019-01203-9

Poldrack, R. A., Huckins, G., & Varoquaux, G. (2020). Establishment of Best Practices for Evidence for Prediction: A Review. *JAMA Psychiatry*, *77*(5), 534–540. https://doi.org/10.1001/jamapsychiatry.2019.3671

Prasartwuth, O., Taylor, J. L., & Gandevia, S. C. (2005). Maximal force, voluntary activation and muscle soreness after eccentric damage to human elbow flexor muscles. *The Journal of Physiology*, *567*(Pt 1), 337–348. https://doi.org/10.1113/jphysiol.2005.087767

Rabinowicz, A., & Rosset, S. (2020). Assessing prediction error at interpolation and extrapolation points. *Electronic Journal of Statistics*, *14*(1). https://doi.org/10.1214/19-EJS1666

Raita, Y., Camargo, C. A., Liang, L., & Hasegawa, K. (2021). Big Data, Data Science, and Causal Inference: A Primer for Clinicians. *Frontiers in Medicine*, *8*, 678047. https://doi.org/10.3389/fmed.2021.678047

Ratamess, N. A., Alvar, B. A., Evetouch, T. K., Housh, T. J., Kibler, W. B., Kraemer, W. J., & Triplett, N. T. (2009). American College of Sports Medicine position stand. Progression models in resistance training for healthy adults. *Medicine and Science in Sports and Exercise*, *41*(3), 687–708. https://doi.org/10.1249/MSS.0b013e3181915670

Reid, M. B. (2016). Reactive Oxygen Species as Agents of Fatigue. *Medicine and Science in Sports and Exercise*, *48*(11), 2239–2246. https://doi.org/10.1249/MSS.0000000000001006

Reid, M. B., Khawli, F. A., & Moody, M. R. (1993). Reactive oxygen in skeletal muscle. Iii. Contractility of unfatigued muscle. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *75*(3), 1081–1087. https://doi.org/10.1152/jappl.1993.75.3.1081

Reynolds, J. M., Gordon, T. J., & Robergs, R. A. (2006). Prediction of One Repetition Maximum Strength from Multiple Repetition Maximum Testing and Anthropometry. *Journal of Strength and Conditioning Research*, *20*(3), 584–592. https://doi.org/10.1519/00124278-200608000-00020

Ribeiro, A. S., Dos Santos, E. D., Nunes, J. P., & Schoenfeld, B. J. (2019). Acute Effects of Different Training Loads on Affective Responses in Resistance-trained Men. *International Journal of Sports Medicine*, *40*(13), 850–855. https://doi.org/10.1055/a-0997-6680

Ribeiro Neto, F., Guanais, P., Dornelas, E., Coutinho, A. C. B., & Costa, R. R. G. (2017). Validity of one-repetition maximum predictive equations in men with spinal cord injury. *Spinal Cord*, *55*(10), 950–956. https://doi.org/10.1038/sc.2017.49

Richens, B., & Cleather, D. J. (2014). The relationship between the number of repetitions performed at given intensities is different in endurance and strength trained athletes. *Biology of Sport*, *31*(2), 157–161. https://doi.org/10.5604/20831862.1099047

Ritti-Dias, R. M., Avelar, A., Salvador, E. P., & Cyrino, E. S. (2011). Influence of previous experience on resistance training on reliability of one-repetition maximum test. *Journal of Strength and Conditioning Research*, *25*(5), 1418–1422. https://doi.org/10.1519/JSC.0b013e3181d67c4b

Roberts, T. J., Eng, C. M., Sleboda, D. A., Holt, N. C., Brainerd, E. L., Stover, K. K., Marsh, R. L., & Azizi, E. (2019). The Multi-Scale, Three-Dimensional Nature of Skeletal Muscle Contraction. *Physiology (Bethesda, Md.)*, *34*(6), 402–408. https://doi.org/10.1152/physiol.00023.2019

Rodríguez-Rosell, D., Yáñez-García, J. M [Juan Manuel], Sánchez-Medina, L., Mora-Custodio, R., & González-Badillo, J. J. (2020). Relationship Between Velocity Loss and Repetitions in Reserve in the Bench Press and Back Squat Exercises. *Journal of Strength and Conditioning Research*, *34*(9), 2537–2547. https://doi.org/10.1519/JSC.0000000000002881

Roelands, B., & Meeusen, R. (2010). Alterations in central fatigue by pharmacological manipulations of neurotransmitters in normal and high ambient temperature. *Sports Medicine (Auckland, N.Z.)*, *40*(3), 229–246. https://doi.org/10.2165/11533670-000000000-00000

Roy, B. D., & Tarnopolsky, M. A. (1998). Influence of differing macronutrient intakes on muscle glycogen resynthesis after resistance exercise. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *84*(3), 890–896. https://doi.org/10.1152/jappl.1998.84.3.890

Rozand, V., Cattagni, T., Theurel, J., Martin, A., & Lepers, R. (2015). Neuromuscular fatigue following isometric contractions with similar torque time integral. *International Journal of Sports Medicine*, *36*(1), 35–40. https://doi.org/10.1055/s-0034-1375614

Ruotsalainen, I., Ahtiainen, J. P., Kidgell, D. J., & Avela, J. (2014). Changes in corticospinal excitability during an acute bout of resistance exercise in the elbow flexors. *European Journal of Applied Physiology*, *114*(7), 1545–1553. https://doi.org/10.1007/s00421-014-2884-z

Sadamoto, T., Bonde-Petersen, F., & Suzuki, Y. (1983). Skeletal muscle tension, flow, pressure, and EMG during sustained isometric contractions in humans. *European Journal of Applied Physiology and Occupational Physiology*, *51*(3), 395–408. https://doi.org/10.1007/BF00429076

Sahlin, K. (2014). Muscle energetics during explosive activities and potential effects of nutrition and training. *Sports Medicine (Auckland, N.Z.)*, *44 Suppl 2*, S167-73. https://doi.org/10.1007/s40279-014-0256-9

Sahlin, K., & Broberg, S. (1990). Adenine nucleotide depletion in human muscle during exercise: Causality and significance of AMP deamination. *International Journal of Sports Medicine*, *11 Suppl 2*, S62-7. https://doi.org/10.1055/s-2007-1024856

Sakamoto, A., & Sinclair, P. J. (2006). Effect of movement velocity on the relationship between training load and the number of repetitions of bench press. *Journal of Strength and Conditioning Research*, *20*(3), 523–527. https://doi.org/10.1519/16794.1

Salles, B. F. de, Simão, R., Miranda, F., Da Novaes, J. S., Lemos, A., & Willardson, J. M. (2009). Rest interval between sets in strength training. *Sports Medicine (Auckland, N.Z.)*, *39*(9), 765–777. https://doi.org/10.2165/11315230-000000000-00000

Sánchez-Medina, L., & González-Badillo, J. J. (2011). Velocity loss as an indicator of neuromuscular fatigue during resistance training. *Medicine and Science in Sports and Exercise*, *43*(9), 1725–1734. https://doi.org/10.1249/MSS.0b013e318213f880

Sanders, N. (2019). A Balanced Perspective on Prediction and Inference for Data Science in Industry. *Harvard Data Science Review*, *1*(1). https://doi.org/10.1162/99608f92.644ef4a4

Santos, W. D. N. D., Vieira, C. A., Bottaro, M., Nunes, V. A., Ramirez-Campillo, R., Steele, J., Fisher, J. P., & Gentil, P. (2021). Resistance Training Performed to Failure or Not to Failure Results in Similar Total Volume, but With Different Fatigue and Discomfort Levels. *Journal of Strength and Conditioning Research*, *35*(5), 1372–1379. https://doi.org/10.1519/JSC.0000000000002915

Santos-Junior, R., & Franchini, E. (2021). Developing strength-endurance for combat sports athletes. *Revista De Artes Marciales Asiáticas*, *16*(1s), 174–191. https://doi.org/10.18002/rama.v16i1s.7004

Schoenfeld, B. J., Grgic, J., van Every, D. W., & Plotkin, D. L. (2021). Loading Recommendations for Muscle Strength, Hypertrophy, and Local Endurance: A Re-Examination of the Repetition Continuum. *Sports (Basel, Switzerland)*, *9*(2). https://doi.org/10.3390/sports9020032

Schwingel, P. A., Porto, Y. C., Dias, M. C. M., Moreira, M. M., & Zoppi, C. C. (2009). Predicting one repetition maximum equations accuracy in paralympic rowers with motor disabilities. *Journal of Strength and Conditioning Research*, *23*(3), 1045–1050. https://doi.org/10.1519/JSC.0b013e3181a06356

Scott, B. R., Duthie, G. M., Thornton, H. R., & Dascombe, B. J. (2016). Training Monitoring for Resistance Exercise: Theory and Applications. *Sports Medicine*, *46*(5), 687–698. https://doi.org/10.1007/s40279-015-0454-0

Scott, C. B., Leighton, B. H., Ahearn, K. J., & McManus, J. J. (2011). Aerobic, anaerobic, and excess postexercise oxygen consumption energy expenditure of muscular endurance and strength: 1-set of bench press to muscular fatigue. *Journal of Strength and Conditioning Research*, *25*(4), 903–908. https://doi.org/10.1519/JSC.0b013e3181c6a128

Sejersted, O. M., Hargens, A. R., Kardel, K. R., Blom, P., Jensen, O., & Hermansen, L. (1984). Intramuscular fluid pressure during isometric contraction of human skeletal muscle. *Journal of Applied Physiology: Respiratory, Environmental and Exercise Physiology*, *56*(2), 287–295. https://doi.org/10.1152/jappl.1984.56.2.287

Shield, A., & Zhou, S. (2004). Assessing voluntary muscle activation with the twitch interpolation technique. *Sports Medicine (Auckland, N.Z.)*, *34*(4), 253–267. https://doi.org/10.2165/00007256-200434040-00005

Shimano, T., Kraemer, W. J., Spiering, B. A., Volek, J. S., Hatfield, D. L., Silvestre, R., Vingren, J. L., Fragala, M. S., Maresh, C. M., Fleck, S. J., Newton, R. U., Spreuwenberg, L. P. B., & Häkkinen, K. (2006). Relationship between the number of repetitions and selected percentages of one repetition maximum in free weight exercises in trained and untrained men. *Journal of Strength and Conditioning Research*, *20*(4), 819–823. https://doi.org/10.1519/R-18195.1

Sinoway, L. I., Rea, R. F., Mosher, T. J., Smith, M. B., & Mark, A. L. (1992). Hydrogen ion concentration is not the sole determinant of muscle metaboreceptor responses in humans. *The Journal of Clinical Investigation*, *89*(6), 1875–1884. https://doi.org/10.1172/JCI115792

Souron, R., Voirin, A.-C., Kennouche, D., Espeit, L., Millet, G. Y., Rupp, T., & Lapole, T. (2020). Task failure during sustained low-intensity contraction is not associated with a critical amount of central fatigue. *Scandinavian Journal of Medicine & Science in Sports*, *30*(12), 2329–2341. https://doi.org/10.1111/sms.13815

Sprey, J. W. C., Ferreira, T., Lima, M. V. de, Duarte, A., Jorge, P. B., & Santili, C. (2016). An Epidemiological Profile of CrossFit Athletes in Brazil. *Orthopaedic Journal of Sports Medicine*, *4*(8), 2325967116663706. https://doi.org/10.1177/2325967116663706

Steele, J. (2021). What is (perception of) effort? Objective and subjective effort during attempted task performance. *PsyArχiv (Preprint).* Advance online publication. https://doi.org/10.31234/osf.io/kbyhm

Steele, J., Endres, A., Fisher, J. P., Gentil, P., & Giessing, J. (2017). Ability to predict repetitions to momentary failure is not perfectly accurate, though improves with resistance training experience. *PeerJ*, *5*, e4105. https://doi.org/10.7717/peerj.4105

Steele, J., Fisher, J. P., Giessing, J., & Gentil, P. (2017). Clarity in reporting terminology and definitions of set endpoints in resistance training. *Muscle & Nerve*, *56*(3), 368–374. https://doi.org/10.1002/mus.25557

Steinbacher, P., & Eckl, P. (2015). Impact of oxidative stress on exercising skeletal muscle. *Biomolecules*, *5*(2), 356–377. https://doi.org/10.3390/biom5020356

Stone, M. H., & O'Bryant, H. S. (1987). *Weight training: A scientific approach*. Burgess International Group.

Stone, M. H., Stone, M. E., Sands, W. A., Pierce, K. C., Newton, R. U., Haff, G. G., & Carlock, J. (2006). Maximum Strength and Strength Training—A Relationship to Endurance? *Strength and Conditioning Journal*, *28*(3), 44. https://doi.org/10.1519/1533-4295(2006)28[44:MSASTR]2.0.CO;2

Stone, W. J., & Coulter, S. P. (1994). Strength/Endurance Effects From Three Resistance Training Protocols With Women. *Journal of Strength and Conditioning Research*, *8*(4), 231. https://doi.org/10.1519/1533-4287(1994)008<0231:SEEFTR>2.3.CO;2

Stutzig, N., & Siebert, T. (2017). Assessment of the H-reflex at two contraction levels before and after fatigue. *Scandinavian Journal of Medicine & Science in Sports*, *27*(4), 399–407. https://doi.org/10.1111/sms.12663

Suchomel, T. J., Nimphius, S., Bellon, C. R., Hornsby, G., & Stone, M. H. (2021). Training for Muscular Strength: Methods for Monitoring and Adjusting Training Intensity. *Sports Medicine (Auckland, N.Z.)*, *51*(10), 2051–2066. https://doi.org/10.1007/s40279-021-01488-9

Tan, S., Wang, J., & Liu, S. (2015). Establishment of the Prediction Equations of 1RM Skeletal Muscle Strength in 60- to 75-Year-Old Chinese Men and Women. *Journal of Aging and Physical Activity*, *23*(4), 640–646. https://doi.org/10.1123/japa.2014-0103

Tanimoto, M., & Ishii, N. (2006). Effects of low-intensity resistance exercise with slow movement and tonic force generation on muscular function in young men. *Journal of Applied Physiology (Bethesda, Md. : 1985)*, *100*(4), 1150–1157. https://doi.org/10.1152/japplphysiol.00741.2005

Tardioli, A., Malliaras, P., & Maffulli, N. (2012). Immediate and short-term effects of exercise on tendon structure: Biochemical, biomechanical and imaging responses. *British Medical Bulletin*, *103*(1), 169–202. https://doi.org/10.1093/bmb/ldr052

Terzis, G., Spengos, K., Manta, P., Sarris, N., & Georgiadis, G. (2008). Fiber type composition and capillary density in relation to submaximal number of repetitions in resistance exercise. *Journal of Strength and Conditioning Research*, *22*(3), 845–850. https://doi.org/10.1519/JSC.0b013e31816a5ee4

Tesch, P. A. (1988). Skeletal muscle adaptations consequent to long-term heavy resistance exercise. *Medicine and Science in Sports and Exercise*, *20*(5 Suppl), S132-4. https://doi.org/10.1249/00005768-198810001-00008

Thomas, K., Brownstein, C. G., Dent, J., Parker, P., Goodall, S., & Howatson, G. (2018). Neuromuscular Fatigue and Recovery after Heavy Resistance, Jump, and Sprint Training. *Medicine and Science in Sports and Exercise*, *50*(12), 2526–2535. https://doi.org/10.1249/MSS.0000000000001733

Tucker, J. E., Pujol, T. J., Elder, C. L., Nahikian-Nelms, M. L., Barnes, J. T., & Langenfeld, M. E. (2006). One-Repetition Maximum Prediction Equation for Traditional College-Age Novice Female. *Medicine and Science in Sports and Exercise*, *38*(5), 293.

Vanhatalo, A., Jones, A. M., & Burnley, M. (2011). Application of critical power in sport. *International Journal of Sports Physiology and Performance*, *6*(1), 128–136. https://doi.org/10.1123/ijspp.6.1.128

Verkhoshansky, Y., & Siff, M. C. (2009). *Supertraining*. Verkhoshansky.

Vianna, J. M., Lima, J. P., Saavedra, F. J., & Reis, V. M. (2011). Aerobic and Anaerobic Energy During Resistance Exercise at 80% 1RM. *Journal of Human Kinetics*, *29A*, 69–74. https://doi.org/10.2478/v10078-011-0061-6

Vieira, A., Blazevich, A., Souza, N., Celes, R., Alex, S., Tufano, J. J., & Bottaro, M. (2018). Acute changes in muscle thickness and pennation angle in response to work-matched concentric and eccentric isokinetic exercise. *Applied Physiology, Nutrition, and Metabolism = Physiologie Appliquee, Nutrition Et Metabolisme*, *43*(10), 1069–1074. https://doi.org/10.1139/apnm-2018-0055

Waldmann, P. (2019). On the Use of the Pearson Correlation Coefficient for Model Evaluation in Genome-Wide Prediction. *Frontiers in Genetics*, *10*, 899. https://doi.org/10.3389/fgene.2019.00899

Ware, J. S., Clemens, C. T., Mayhew, J. L., & Johnston, T. J. (1995). Muscular endurance repetitions to predict bench press and squat strength in college football players. *Journal of Strength and Conditioning Research*, *9*(2), 99–103.

Wathen, D. (1994). Load assignment. In T. R. Baechle (Ed.), *Essentials of strength training and conditioning* (pp. 435–439). Human Kinetics.

Weakley, J., Mann, J. B., Banyard, H. G., McLaren, S., Scott, T., & García-Ramos, A. (2021). Velocity-Based Training: From Theory to Application. *Strength & Conditioning Journal*, *43*(2), 31–49. https://doi.org/10.1519/SSC.0000000000000560

Welday, J. (1988). Should you check for strength with periodic max lifts? *Scholastic Coach*, *57*(9), 49–68.

West, W., Hicks, A., McKelvie, R., & O'Brien, J. (1996). The relationship between plasma potassium, muscle membrane excitability and force following quadriceps fatigue. *Pflugers Archiv : European Journal of Physiology*, *432*(1), 43–49. https://doi.org/10.1007/s004240050103

Westerblad, H., & Allen, D. G. (1993). The influence of intracellular pH on contraction, relaxation and Ca2+i in intact single fibres from mouse muscle. *The Journal of Physiology*, *466*, 611–628.

Westerblad, H., Allen, D. G., & Lännergren, J. (2002). Muscle fatigue: Lactic acid or inorganic phosphate the major cause? *News in Physiological Sciences : An International Journal of Physiology Produced Jointly by the International Union of Physiological Sciences and the American Physiological Society*, *17*, 17–21. https://doi.org/10.1152/physiologyonline.2002.17.1.17

Westerblad, H., Bruton, J. D., & Katz, A. (2010). Skeletal muscle: Energy metabolism, fiber types, fatigue and adaptability. *Experimental Cell Research*, *316*(18), 3093–3099. https://doi.org/10.1016/j.yexcr.2010.05.019

Whisenant, M. J., Panton, L. B., East, W. B., & Broeder, C. E. (2003). Validation of submaximal prediction equations for the 1 repetition maximum bench press test on a group of collegiate football players. *Journal of Strength and Conditioning Research*, *17*(2), 221–227.

Wilburn, D. T., Machek, S. B., Cardaci, T. D., Hwang, P. S., & Willoughby, D. S. (2020). Acute Maltodextrin Supplementation During Resistance Exercise. *Journal of Sports Science & Medicine*, *19*(2), 282–288.

Winwood, P. W., Pritchard, H. J., Wilson, D., Dudson, M., & Keogh, J. W. L. (2019). The Competition-Day Preparation Strategies of Strongman Athletes. *Journal of Strength and Conditioning Research*, *33*(9), 2308–2320. https://doi.org/10.1519/JSC.0000000000003267

Wolosker, H., Rocha, J. B., Engelender, S., Panizzutti, R., Miranda, J. de, & Meis, L. de (1997). Sarco/endoplasmic reticulum Ca2+-ATPase isoforms: Diverse responses to acidosis. *The Biochemical Journal*, *321 (Pt 2)*, 545–550. https://doi.org/10.1042/bj3210545

Wood, T. M., Maddalozzo, G. F., & Harter, R. A. (2002). Accuracy of Seven Equations for Predicting 1-RM Performance of Apparently Healthy, Sedentary Older Adults. *Measurement in Physical Education and Exercise Science*, *6*(2), 67–94. https://doi.org/10.1207/S15327841MPEE0602_1

Zając, A., Chalimoniuk, M., Maszczyk, A., Gołaś, A., & Lngfort, J. (2015). Central and Peripheral Fatigue During Resistance Exercise - A Critical Review. *Journal of Human Kinetics*, *49*, 159–169. https://doi.org/10.1515/hukin-2015-0118

Zatsiorsky, V. M., & Kraemer, W. J. (2006). *Science and practice of strength training* (2. ed.). Human Kinetics.

Zwarts, M. J., & Arendt-Nielsen, L. (1988). The influence of force and circulation on average muscle fibre conduction velocity during local muscle fatigue. *European Journal of Applied Physiology and Occupational Physiology*, *58*(3), 278–283. https://doi.org/10.1007/BF00417263

6 List of Figures

7 List of tables

8 Appendices

8.1 Appendix A: Derivation of eq. 15

The 2-parameters exponential regression model (eq. 15) can be derived from a linear regression model (eq. 11) by applying a natural log transformation to load.

$$\ln(load) = a' + b'\ RTF \qquad | \ e$$

$$load = e^{a' + b'\ RTF} \qquad | \ apply\ product\ rule$$

$$load = e^{a'}\ e^{b'\ RTF} \qquad | \ e^{a'} = a;\ b' = b$$

$$load = a\ e^{b\ RTF}$$

Therefore, when estimating model parameters based on a linear model with load being log-transformed, caution must be taken to recover the intercept parameter *a* when applying the exponential notation of the equation.

8.2 Appendix B: Derivation of eq. 29

The derivation of $\overrightarrow{OS}_{max}$ (eq. 29) requires $\overrightarrow{OA}$ to be expressed as a linear function (eq. 27), and the strength-endurance relationship, as expressed by (Adams & Beam, 2014):

$$load = 1 - 0.025\ n$$

The intersection can then be calculated by equalizing the two functions as follows:

$$\frac{load_a}{n_a}\ n_{lim} = 1 - 0.025\ n_{lim} \qquad | \ \times n_a$$

$$load_a\ n_{lim} = n_a - 0.025\ n_{lim}\ n_a \qquad | + 0.025\ n_{lim}\ n_a$$

$$n_{lim}(load_a + 0.025\ n_a) = n_a \qquad | \div (load_a + 0.025\ n_a)$$

$$n_{lim} = \frac{n_a}{load_a + 0.025\ n_a} \qquad | \ plug\ in\ eq.27$$

$$load_{lim} = \frac{load_a}{n_a}\ \frac{n_a}{load_a + 0.025\ n_a} \qquad | \ solve$$

$$load_{lim} = \frac{load_a}{load_a + 0.025\ n_a}$$

$$\overrightarrow{OS}_{max} = \begin{pmatrix} load_{lim} \\ n_{lim} \end{pmatrix} = \begin{pmatrix} \dfrac{load_a}{load_a + 0.025\ n_a} \\ \dfrac{n_a}{load_a + 0.025\ n_a} \end{pmatrix} \qquad (29)$$

8.3 Appendix C: Derivation of eq. 32

Eq. 32 can be derived from the 2-parameters exponential model function (eq. 15) by assuming a change in the number of RTF (ΔRTF) and intercept (*Δa*), while the curvature parameter *b* is assumed to remain unchanged:

$$load = a\, e^{b\, RTF} \qquad |\, add\ \Delta a\ and\ \Delta RTF$$

$$load = (a + \Delta a)\, e^{b\,(RTF+\Delta RTF)} \qquad |\, ln()$$

$$ln(load) = ln(a + \Delta a) + b\,(RTF + \Delta RTF) \qquad |\, - ln(a + \Delta a)$$

$$ln(load) - ln(a + \Delta a) = b\,(RTF + \Delta RTF) \qquad |\, apply\ division\ rule$$

$$ln\left(\frac{load}{a + \Delta a}\right) = b\,(RTF + \Delta RTF) \qquad |\, \div b$$

$$ln\left(\frac{load}{a + \Delta a}\right)\frac{1}{b} = RTF + \Delta RTF \qquad |\, - RTF$$

$$ln\left(\frac{load}{a + \Delta a}\right)\frac{1}{b} - RTF = \Delta RTF \qquad |\, solve\ eq. 15\ for\ RTF$$

$$ln\left(\frac{load}{a + \Delta a}\right)\frac{1}{b} - ln\left(\frac{load}{a}\right)\frac{1}{b} = \Delta RTF \qquad |\, extract\ \frac{1}{b}$$

$$\frac{1}{b}\left(ln\left(\frac{load}{a + \Delta a}\right) - ln\left(\frac{load}{a}\right)\right) = \Delta RTF \qquad |\, apply\ division\ rule$$

$$\frac{1}{b}\, ln\left(\frac{load}{a + \Delta a}\ \ \frac{a}{load}\right) = \Delta RTF \qquad |\, solve$$

$$\frac{1}{b}\, ln\left(\frac{a}{a + \Delta a}\right) = \Delta RTF \qquad (32)$$

8.4 Appendix D: Derivation of eq. 33

Similar to eq. 31, eq. 33 is the result of intersecting $\overrightarrow{OA}$ with the strength-endurance model, which in this case is an unspecified 2-parameter exponential function (eq. 15). To solve the equation for n_{lim}, it has to be rewritten in Lambert form $f(z) = z\, e^{z}$. Assuming that z is always positive, the equation can then be solved using the principal branch of the Lambert *W* function (W_0).

$$\frac{load_a}{n_a}\, n_{lim} = a\, e^{b\, n_{lim}} \qquad |\times n_a \ \ |\times (e^{b\, n_{lim}})^{-1}$$

$$load_a\, n_{lim}(e^{b\, n_{lim}})^{-1} = \ a\, n_a \qquad |\, substitute: -b\, n_{lim} = z$$

$$load_a \left(-\frac{z}{b}\right) e^z = a\, n_a \qquad |\div load_a \quad |\times(-b)$$

$$z\, e^z = -\frac{a\, b\, n_a}{load_a} \qquad |\ apply\ Lambert\ W_0$$

$$z = W_0\left(-\frac{a\, b\, n_a}{load_a}\right) \qquad |\, substitute\!: z = -b\, n_{lim}$$

$$-b\, n_{lim} = W_0\left(-\frac{a\, b\, n_a}{load_a}\right) \qquad |\ \div(-b)$$

$$n_{lim} = -\frac{1}{b}\, W_0\left(-\frac{a\, b\, n_a}{load_a}\right) \qquad |\, apply\ to\ RE_v = \frac{n_a}{n_{lim}}$$

$$RE_v = \frac{n_a}{n_{lim}} = -b\, n_a\, W_0\left(-\frac{a\, b\, n_a}{load_a}\right)^{-1} \qquad (33)$$

8.5 Appendix E: Derivation of eq. 34

The derivation of eq. 34 follows the same rationale described in section 8.4, except for the strength-endurance profile being expressed as an unspecified reciprocal regression function (eq. 12). To solve for n_{lim}, a quadratic equation has to be applied. Due to n_{lim} being limited to only positive values, the solution of the quadratic equation yielding a negative value can be omitted. Thus, as both parameters in the reciprocal regression model can be assumed to be positive real numbers, to yield the characteristic curvilinear decay of the strength-endurance relationship, the result of the square root of the quadratic equation is always expected to be an additive term.

$$\frac{load_a}{n_a}\, n_{lim} = \frac{1}{a + b\, n_{lim}} \qquad |\times(a + b\, n_{lim}) \quad |\times n_a$$

$$load_a\, n_{lim}(a + b\, n_{lim}) = n_a \qquad |-n_a$$

$$b\, load_a\, {n_{lim}}^2 + a\, load_a\, n_{lim} - n_a = 0 \qquad |\, solve\ for\ n_{lim} \in \mathbb{R}^+$$

$$n_{lim} = \frac{-a\, load_a + \sqrt{a^2\, {load_a}^2 + 4\, b\, load_a\, n_a}}{2\, b\, load_a} \qquad |\ reduce\ by\ load_a$$

$$n_{lim} = \frac{-a + \sqrt{a^2 + \frac{4\, b\, n_a}{load_a}}}{2\, b} \qquad |\, apply\ to\ RE_v = \frac{n_a}{n_{lim}}$$

$$RE_v = \frac{n_a}{n_{lim}} = 2\, b\, n_a \left(\sqrt{a^2 + \frac{4\, b\, n_a}{load_a}} - a\right)^{-1} \qquad (34)$$

8.6 Appendix F: Decision of the Ethics Committee (ref. no. 00461)

Beschluss der Ethikkommission Decision of the Ethics Committee	universität wien Ethikkommission

Antragsteller/Applicant: **Benedikt Mitter, MSc.**
Bearbeitungsnummer/Reference Number: **00461**
Projekttitel/Title of Project: **Validity and reliability of individualized profiles of the strength-endurance continuum**

Die Stellungnahme der Ethikkommission erfolgt aufgrund folgender eingereichter Unterlagen/ The decision of the Ethics Committee is based on the following documents:

13.05.2019

- MITTER_12.05.2019_Antragsformular
- MITTER_12.05.2019_Aushang
- MITTER_12.05.2019_Cover_Letter
- MITTER_12.05.2019_Fragebogen
- MITTER_12.05.2019_TeilnehmerInneninformation

Die Kommission fasst folgenden Beschluss (mit X markiert)/The Ethics Committee has made the following decision (marked with an X):

☒ Zustimmung: Es besteht kein ethischer Einwand gegen die Durchführung der Studien/ Consent: There is no ethical objection to conduct the study as proposed

☐ Negative Beurteilung: Der Antrag wird von der Ethikkommission abgelehnt /Negative evaluation: The proposal is rejected by the Ethics Committee

Unterschrift/Signature

ETHIKKOMMISSION UNIVERSITÄT WIEN

Datum/Date
27.06.2019

Vorsitzender der Ethikkommission/Chair of the Ethics Committee
Univ.-Prof. MMag. DDDr. Martin Voracek

8.7 Appendix G: Decision of the Ethics Committee (ref. no. 00727)

Beschluss der Ethikkommission Decision of the Ethics Committee	universität wien Ethikkommission

Antragsteller*in / Applicant: **Benedikt Mitter, Bakk. MSc**
Bearbeitungsnummer / Reference Number: **00727**
Projekttitel / Title of Project: **Validierung eines Testverfahrens zur Bestimmung von Kraft-Ausdauer Profilen im Bankdrücken**

Die Stellungnahme der Ethikkommission erfolgt aufgrund folgender eingereichter Unterlagen / The decision of the Ethics Committee is based on the following documents:

06.09.2021
- MITTER_06.09.2021_Antragsformular
- MITTER_06.09.2021_Aushang
- MITTER_06.09.2021_Cover_Letter
- MITTER_06.09.2021_Fragebogen
- MITTER_06.09.2021_Teilnehmer_inneninformation

14.12.2021
- MITTER_14.12.2021_Antragsformular
- MITTER_14.12.2021_Teilnehmer_inneninformation

Die Kommission fasst folgenden Beschluss (mit X markiert) / The Ethics Committee has made the following decision (marked with an X):

☒ Zustimmung: Es besteht kein ethischer Einwand gegen die Durchführung der Studien. / Consent: There is no ethical objection to conduct the study as proposed.

☐ Negative Beurteilung: Der Antrag wird von der Ethikkommission abgelehnt. / Negative evaluation: The proposal is rejected by the Ethics Committee.

Inhaltliche Abänderungen müssen der Ethikkommission vorgelegt werden. / Amendments to the content must be presented to the Ethics Committee.

Unterschrift / Signature — Datum / Date

ETHIKKOMMISSION UNIVERSITÄT WIEN

VM

17.01.2022

Vorsitzender der Ethikkommission / Chair of the Ethics Committee
Univ.-Prof. MMag. DDDr. Martin Voracek

9 Declaration of authorship

I hereby declare that I am the sole author of this dissertation, except where due acknowledgment has been made. Direct and indirect sources of information are acknowledged as references.

The manuscript or parts from it have not previously been submitted to qualify for any other academic degree in English or any other language.

Benedikt Mitter