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Early Promise Versus Late Bloomers: A Longitudinal and Multidisciplinary Analysis of Relative Age Effects in an Elite Weightlifting Pathway

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Abstract

Over a series of three studies, we investigated the relative age effect (RAE) across an elite weightlifting pathway, in the context of individual, task, and environmental constraints. Study 1 investigated the influence of gender and bodyweight on RAE. Where previous literature has often assumed success based on selection alone, the current authors also adopted medal success as a more valid indication of attainment. While it might be expected that the presence of weight categories may negate RAE, significant chi^2 effects were robust across developmental stages and weight categories, with some gender-related nuances. Furthermore, multiple logistic regressions revealed RAE to be less prevalent in male athletes who transitioned from non-medalist to medalist ($p < 0.05$). Findings suggest that Q1 athletes, perhaps selected based on early promise as a result of their older status, may not follow through in terms of potential talent at later stages of the pathway and may in fact drop out once maturational biases are no longer in their favor. Study 2 tested this with a longitudinal design to investigate the influence of athlete birth month on progression through the pathway. Results revealed that a higher proportion of Q4 athletes were retained in the pathway. While Q1 athletes were more likely to show early promise, Q4 athletes were more likely to "bloom" and deliver talent later in the pathway. Finally, Study 3 investigated the role of psychological characteristics in accounting for these findings. Sophisticated machine learning techniques differentiated between Q1 and Q4 athletes with an accuracy of 76%, based on psychological determinants of expertise: mastery approach, concern over mistakes, emotional stability, and openness to experience. These findings have important implications for practitioners with regard to talent identification and athlete selection protocols.

Keywords

Relative age effect, Olympic weightlifting, drop-out, talent development, expertise, psychology

Introduction

Sociologist Robert Merton (1968) first popularized the concept of "unintended consequences" to describe often-unforeseen effects of purposeful social action. These unintended consequences occur when humans attempt to exert control on a dynamic, complex, and chaotic universe. One such example is the attempt to apply parity to the complex environment of youth sport by developing athlete cohorts based on predefined age-brackets. In many instances, the social action of trying to create parity can in fact achieve the very opposite (Wattie et al., 2015). The implications of these sport developmental age brackets were first observed by Barnsley et al. (1985) who remarked on an extraordinary linear relationship between “birth-month” and the “proportion of players selected within a national ice hockey program.” The term “relative age effect” (RAE) was adopted to account for this phenomenon and highlights the significant developmental advantages and selection bias for those born earlier in the year within an athlete cohort. While the RAE has been observed across a number of sports (for a meta-analysis see Cobley et al., 2009), there is sufficient evidence to suggest both inter- and intra-sport differences based on a number of multidisciplinary mechanisms. As things stand, the complexity of these bio-psycho-social mechanisms, and subsequent influence on RAE, has likely been underestimated in current literature and warrants further investigation.

The most palpable mechanisms underpinning RAE are arguably biological in nature, with physical advantages associated with early maturation (e.g., enhanced speed, strength, and coordination) influencing athlete selection (Barnsley et al., 1985). Wattie et al. (2015) propose an increased prominence of RAE in sports that are biased toward such physical attributes; e.g., rugby and basketball. Similarly, gender has been identified as an important determinant of RAE, whereby the aforementioned physical advantages of early maturation are often more pronounced in the male population (Okazaki et al., 2011; Schorer et al., 2009). However, it is important to highlight Costello et al.’s (2014) findings, identifying an under-representation of female participants within sport and exercise science literature more broadly. Costello and colleagues subsequently warn against gender disparities within our understanding across the knowledge base. Conscious of this, Smith et al. (2018) conducted a systematic review and meta-analysis to better understand RAE in the female population. Findings highlight the role of development stage and sport context to the prevalence and magnitude of RAEs in females. Thus, part of our rationale behind the current series of studies was to investigate the role of gender in moderating RAE within the sporting context.

A sociological model assimilating a number of pre-existing theories has been used to account for the role of social agents (e.g., coaches and parents) in influencing RAE (Hancock et al., 2013). Hancock et al. suggest that Matthew effects (e.g., “the rich get richer and the poor get poorer”; Merton, 1968), are perpetuated in sport by social mediators. For example, parents enrolling chronologically older children into sports earlier and thus, inadvertently facilitating more opportunities for them. Similarly, Hancock and colleagues use Pygmalion effects (Rosenthal & Jacobson, 1968) to describe a type of self-fulfilling prophecy whereby greater expectations from significant others leads to greater results; e.g., a coach facilitating increased game time or individualized coaching based on enhanced expectations of a physically greater developed athlete. These social agents may also include policy makers. One such example of this is the presence of weight categories within a sport; e.g., weightlifting or combat sports. Researchers have hypothesized an elimination of RAE in sports where weight categories are in existence (see Albuquerque et al., 2016). Mixed findings limit the extent to which we can guide practitioners, and researchers are yet to investigate this beyond combat sports and consider between-weight category effects (e.g., Delorme, 2014). It is possible that any intra-sport differences as a function of weight category may have acted as an extraneous variable, thus confounding overall findings. This methodological shortcoming warrants further scrutiny. Fukuda et al. (2017) attribute contradictory findings across combat sports (which typically adopt weight categories) to distinctions between grappling-based sports (e.g., judo or wrestling) and striking-based sports (e.g., boxing or taekwondo), further emphasizing the need for sport-specific interrogation. Furthermore, the somewhat paradoxical hypotheses surrounding sports biased toward physicality (where one would expect an increased prevalence of RAE), combined with the notion that the presence of weight categories within a sport's structure may in fact eliminate RAE (Delorme, 2014), make the sport of weightlifting worthy of investigation.

In addition to an athlete's physical characteristics and the unintended consequences of social agents within sport, psychological mechanisms have also been identified as important contributing factors to RAE. Where Pygmalion effects refer to the influence on the behavior of social agents once expectations about an athlete have been set, Galatea effects (Merton, 1957) refer to the expectations and behaviors of the athlete themselves in a self-fulfilling prophecy; e.g., raised confidence or work ethic. Psychological hypotheses to account for RAE findings have also emerged when investigating the super-elite end of the performance spectrum (Gibbs et al., 2012; Jones et al., 2018; McCarthy et al., 2016), where reversal or inverse effects emerge. Gibbs et al. (2011) term this "the rise of the underdog" whereby relatively younger players benefit psychologically from longstanding exposure to higher levels of challenge. This notion is supported by a host of literature underlying the paradoxical benefits of adversity or a "rocky road" (Collins & MacNamara, 2012; Hardy et al., 2017; Rees et al., 2016). However, it is important to note that psychological underpinnings of RAE remain hypothetical in nature.

Wattie et al. (2015) argue that the RAE is likely a more complex interaction between individuals and their environment. They propose a developmental systems model, based on Newell's (1986) constraints approach to motor learning, whereby individual constraints (such as birth date and gender), interact with task constraints (such as sport type, expertise level and positional role) and environmental constraints (such as sport policy, structure, and continent) to influence the ensuing RAE. However, despite the proposal that the RAE is a result of a set of complex and multidisciplinary interactions, the phenomenon is typically investigated using cross-sectional approaches and neglects to consider the likely dynamic nature of this phenomenon over time (Faber et al., 2019).

A further oversight of RAE literature is the assumptions of success based on selection to, or presence on, a team alone. To the authors' knowledge, the only paper attempting to address this limitation is Jones et al. (2018). Here the authors used a selection of "performance" criteria developed in collaboration with national coaches to identify super-elite level cricketers and rugby players when investigating RAE. While this helped address the limitations of investigating the RAE against a single performance criterion, the nature of the data investigated was cross-sectional.

Over the course of three studies, we addressed the aforementioned limitations and provided the first test of Wattie et al.'s (2015) developmental systems model. Specifically, we investigated the RAE in the context of individual, task, and environmental constraints. Individual constraints included an athlete's birthdate, gender, development stage, performance success and psychological make-up. Environmental constraints included the bodyweight classifications imposed on the sport through policy makers, and task constraints included the sport-specific nature of analysis in weightlifting. The data were investigated using a longitudinal approach to afford both an empirical understanding of the dynamic nature of RAE and to scrutinize athlete retention and transition through the pathway as a function of birth quarter.

Study 1

The rationale behind Study 1 was threefold: First, the authors wanted to investigate individual constraints of RAE, including gender and bodyweight classification; second, we wanted to investigate RAE across different development stages of a talent pathway; and third, we wanted to investigate RAE more closely in line with athletic performance by using medal attainment as a more objective measure of success.

We hypothesized intra-sport differences in RAE, whereby a stronger RAE would exist in higher weight categories. This is in line with literature demonstrating more pronounced RAEs in sports biased toward physicality (Wattie et al., 2015). Furthermore, based on the increased prominence of physical developments following biological maturation in males, we expected to see a more pronounced RAE in male athletes (see also Schorer et al., 2009). In line with McCarthy et al. (2016), we expected these findings to be more pronounced earlier in the pathway where maturation differences are more prominent. Finally, if presence within an elite pathway is not an adequate reflection of success, then we would expect to find RAE differences as a function of medal success.

Methods

Participants

Research was conducted in line with institutional ethical guidelines. Data were collected from the publicly available competition results archive on the International Weightlifting Federation's (IWF) webpage (www.iwf.com). This included a total of 45,988 athlete results from all international youth, junior and senior events held between 1998 and 2018. Youth events included results from athletes ranging from 13 to 17 years of age, junior events included results from athletes ranging from 15 to 20 years, and senior events from athletes ≥15 years. Given the considerable overlap between age groups, athletes were limited to a single entry in the dataset by selecting the entry in which they were ranked the highest. The resulting dataset contained a sample of 12,855 athletes (F = 4,867 athletes [38% of overall sample], M = 7,988 [62% of overall sample]). This included results from a total of 280 competitions. All were IWF commissioned, meaning that athletes were only eligible to compete through meeting qualification criteria recognized by either the IWF, the Commonwealth and, Olympic committees, or respective continental federations. Competitions were tiered such that the highest possible level was the Olympic Games, followed by World Championships, Commonwealth Games, and respective continental championships (i.e., African, American, Asian, European, and Oceania championships). Table 1 shows a breakdown of specific bodyweight categories by age group and gender.

For the purpose of the current study, bodyweight categories were grouped into one of three category types for their respective gender and age group: lightweight (for the lightest two categories), middleweight (for the middle three categories), and heavyweight (for the heaviest two or three categories depending on whether there were seven or eight categories in total, respectively; see Table 1 (p. 355). This enabled a sample size that could appropriately test for an influence of bodyweight classification on RAE.

Procedure

Athlete birthdates were classified into birth quartiles in accordance with the age group cut-off dates used by the IWF. As such, athletes whose birthdates fell between January 1 and March 31 were assigned as quartile 1 (Q1), April 1 to June 31 as quartile 2 (Q2), July 1 to September 30 as quartile 3 (Q3), and October1 to December 31 as quartile 4 (Q4). In addition to bodyweight classification, each athlete was assigned a label based on whether or not their performance had earned them a medal in their respective category. Consequently, athletes who placed 1st, 2nd or 3rd were assigned the label "medalist," while athletes who placed 4th or higher were assigned with the label "non-medalist."

Data Analysis

Data processing and analysis was performed using R version 3.5.2 in R Studio. All analyses were performed using functions from the base R package (R Core Team, 2018). Chi^2 goodness of fit tests were performed on the distribution of the birth quartiles within each of the gender and bodyweight classifications as listed in Table 1. Logistic regression was performed in order to determine the relative risk size of any RAE found. In line with comparisons previously used in the RAE literature (Till et al., 2010), odds ratios and 95% confidence intervals were calculated for Q1 vs Q4, Q2 vs Q4, Q3 vs Q4, as well as half year (first half [H1] vs second half [H2]) comparisons. This enabled the assessment of distributions in the context of the RAE risk to take place across all quartiles.

Finally, to further explore any potential interactive effects of bodyweight classification and medal success (medalist / non-medalist) on RAEs, separate multiple logistic regression analyses was performed for each gender using the distribution of Q1 birthdates relative to Q4 as the dependent variable, and age group (i.e., youth, junior, senior), bodyweight classification, and medal success as predictor variables. For each predictor variable, the level of the lowest order was coded as the baseline level for that variable. Specifically, the "youth," "lightweight," and "non-medalist" levels were coded as the baseline level for the age-group, bodyweight classification, and medal success predictor variables, respectively, meaning that any coefficients reported in the model are relative to the baseline parameter. For all tests used, statistical significance was determined at the 95% confidence level.

Results

Table 2 (p. 355) shows results for the birthdate distributions, chi^2 analyses, respective odds ratios, and confidence intervals as a function of age group and bodyweight classification. Significant chi^2 effects were observed across all age groups and weight categories with the exception of female junior heavyweight and lightweight categories, respectively ($X^2 = 3.87$, $p = 0.338$; $X^2 = 5.21$, $p = 0.157$). This is further supported by inspection of 95% confidence intervals for the odds ratios. Results for the logistic regression model are displayed in Tables 3 (p. 356) and 4 (p. 357) for males and females, respectively and visually represented in Figure 1.

Females

For females, a significant developmental stage interaction x bodyweight x medal success ($B = -1.03$, $SE = 0.52$, $z = -2$, $p < 0.05$) was observed, which suggests opposite RAE's (measured as the log odds of Q1 membership relative to Q4 membership) were observed when comparing the middleweight and lightweight categories in the transition from youth to junior; and that this relationship was only apparent in medalling athletes (see top left plot of Figure 1). No other significant main effects or interactions were observed ($p > 0.05$).

Males

For males, results revealed a main effect for medal success ($B = -0.535$, $SE = 0.27$, $z = -1.996$, $p < 0.05$), which suggests that the RAE was stronger in youth non-medalists relative to youth medalists. Additionally, a significant developmental stage x bodyweight x medal success interaction ($B = -1.02$, $SE = 0.43$, $z = -2.35$, $p < 0.05$) was observed. This interaction suggests that opposite RAE relationships were observed when comparing middleweights and lightweights in the transition from youth to senior; and, similar to the female analysis, this relationship was observed only in the medalists (see Figure 1). No other significant interactions were observed ($p > 0.05$).

Discussion

The rationale behind Study 1 was to provide a more comprehensive investigation of RAE in a sport that could be broken down into its respective categories; i.e., gender, bodyweight, developmental stage, and subsequent performance success. These respective breakdowns were all based on theoretical rationale; e.g., gender differences grounded in the notion that biological maturation may exacerbate physical attributes more so in males than females (Aune et al., 2018), a more pronounced RAE in higher weight categories, the same way in which it is for sports biased toward enhanced physical attributes (Wattie et al., 2015), and a reduced prevalence of RAE at later developmental stages of the pathway in line with and the notion that any advantages of early maturation eventually "level out" as athletes get closer to and eventually move beyond maturity (Faber et al., 2019).

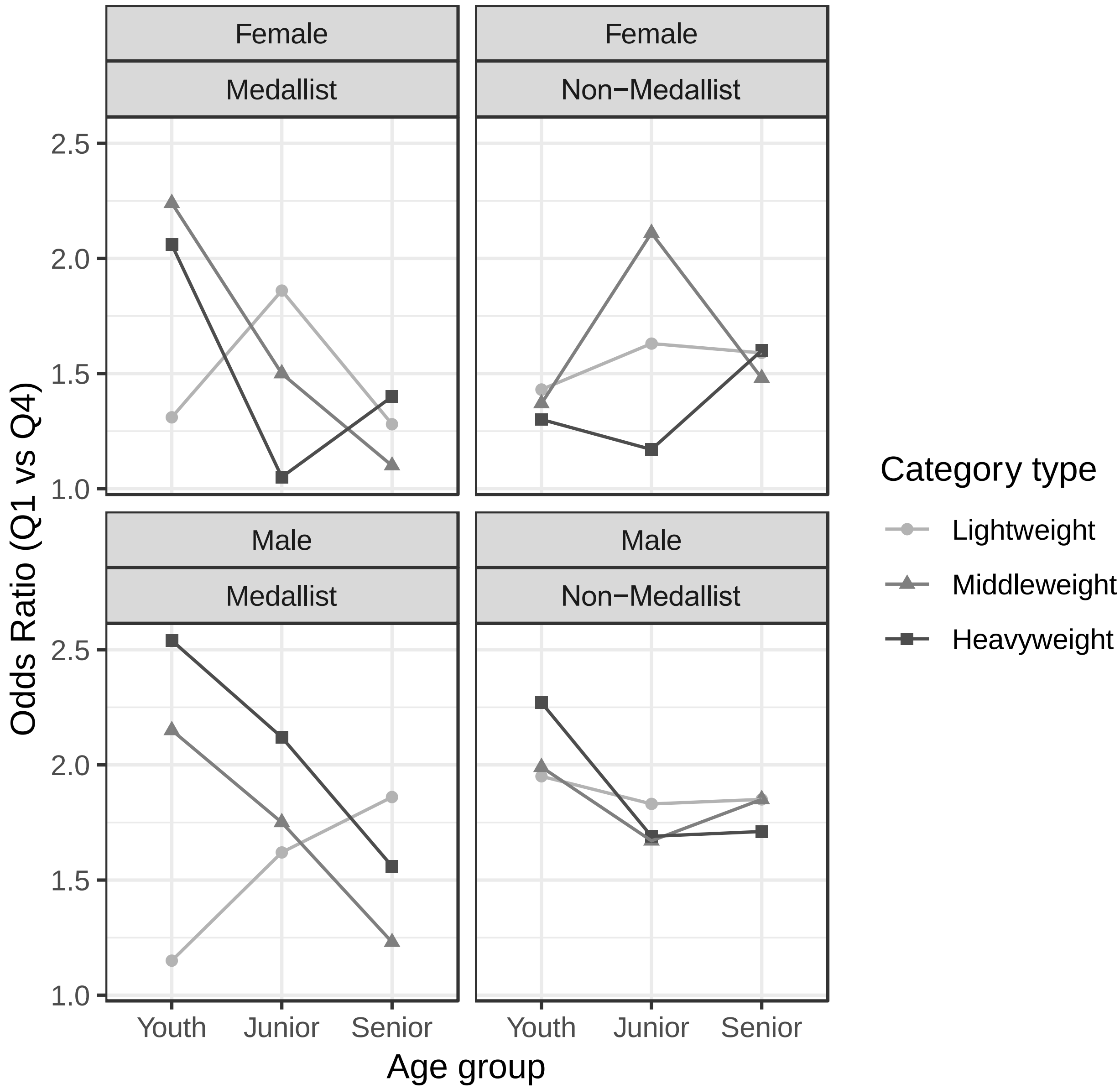

Figure 1. Odds ratios for each age group and weight category type in both male and female medalists and non-medalists.

Overall results revealed a significant RAE biased toward Q1 athletes across all developmental stages and weight categories, excluding the female youth lightweight and female junior heavyweight categories. This suggests that the existence of weight categories within a sport's structure does not in itself diminish RAE. However, with regard to performance measures, this effect was nuanced throughout bodyweight categories, gender, and development stages (see Table 2).

As per previous literature, findings were consistent with the notion that RAE may reduce as a function of chronological age (e.g., Faber et al., 2019), with some gender-related nuances. For females, RAE diminished between youth (13-17yrs) and junior (15-20yrs) levels, but only for athletes in the middleweight and heavyweight categories who medalled. Male lifters also showed a reduced prevalence of the RAE between youth and senior medalists in the middleweight and heavyweight categories. Overall results seem to show a clearer trend within male compared to female findings, which is in line with hypotheses presented by Malina et al. (2004), whereby physical maturational differences between males and females may influence males and subsequently RAE more so than females.

With regard to bodyweight categories, where we hypothesized a stronger RAE at higher categories, we see this effect only in youth lifters within male athletes in particular (see Figure 1). Overall findings actually suggest a reduced prevalence of the RAE at higher weight categories as athletes progress through the pathway. It is possible this is a consequence of Q1 athletes being more likely to drop out at later stages of the pathway when maturational biases are no longer in their favor and this effect is more pronounced at the higher weight categories.

A similar pattern emerges with regard to medal success; i.e., RAE is more prevalent in athletes who do not medal as opposed to those who do. It is only at the youth level where we see a stronger RAE in medalists compared to non-medalists (for middleweight lifters only). Together, these findings suggest that Q1 athletes, perhaps selected based on early promise as a result of physical superiority, may not be following through in terms of their potential talent at later stages of the pathway. Lightweight lifters tended to show a slightly different pattern, with medalling male lifters more likely to show a stronger RAE as they progress through the pathway. This may, however, be a result of middleweight athletes transitioning down to a lower weight category as they get older.

Although a longitudinal design investigating different developmental stages of the pathway was used, it could still be argued that it was a cross-section of the dataset, and so the observations were limited to between-group comparisons. Thus, the findings may not extend to any effects athletes may experience as they progress throughout the system. Additionally, we were compelled to make assumptions surrounding athlete drop-out without empirical data to support these hypotheses. Study 2 sought to incorporate a refined longitudinal observation of athletes who had competed in youth right through to senior competitions. In short, we wanted to investigate athlete transition, and subsequently retention, across developmental stages of the pathway in order to better understand the RAEs observed in Study 1.

Study 2

Study 2 investigated the retention of athletes born in different birth quarters, as they transitioned across different stages of the pathway; i.e., starting at youth before progressing through to junior and ultimately senior age groups. Typically, we would expect to see increased drop-out of Q4 athletes as they struggle to survive in a system where their physical development is inferior to their peers (see Delorme et al., 2010). These mechanisms would normally contribute to an increased prominence of Q1 athletes within a system; i.e., the RAE. However, findings of Study 1 suggested a reduction in prevalence of the RAE in weightlifting as athletes progressed through the pathway, especially at the higher weight categories. Therefore, we wanted to determine whether this was a result of Q1 athletes dropping out of the system at later stages of the pathway and subsequently not fulfilling their "early promise." We also wanted to investigate whether Q4 athletes who are able to survive early stages of the pathway are, by doing so, provided with the additional time they need to flourish into "late bloomers." We adopted a longitudinal approach to investigate athlete retention as a function of birth quarter, between different stages of the pathway. Data were analyzed in relation to any transition between bodyweight categories and changes in medal success.

Methods

The dataset was the same for Study 2 as it was for Study 1, with one exception: athletes who had competed in an IWF event in the youth age group were tracked longitudinally throughout the dataset in order assess the retention of these athletes, and whether or not the retention in these athletes was in any way influenced by the RAE.

Participants

Athletes were retained in the dataset based on their appearance in at least one IWF competition in the youth age group. In order to ensure athletes in the dataset had time to progress from youth to senior competition levels, only youth events prior to 2014 were included and athletes born prior to the January 1, 2000. For any athletes appearing in more than one youth competition, the entry with the highest respective rank position followed by the highest bodyweight category (in the case of a tied rank position) were used as criterion variables to filter the dataset. Consequently, a total of 3,175 athletes were included in the analysis.

Procedure

Birth quartiles, bodyweight categories, and medal success for each athlete were determined using the same criteria outlined in Study 1. Athletes were tracked longitudinally by filtering the names of all athletes appearing in the junior competitions in the dataset by the names of the athletes in the youth sample. Any athlete who appeared in this filtered dataset, and for whom the date of the junior competition was later than the respective youth competition, were retained for subsequent analysis. Any athlete in the youth sample that did not appear in the junior or subsequent senior sample was assumed to have dropped out from IWF competitions, and thus did not form part of the retained sample. This process was then repeated for the retained junior sample by filtering this dataset against all senior competitions. This resulted in a total of 907 athletes identified as having progressed from junior through to senior competition.

For each athlete in the retained sample at both junior and senior age groups, bodyweight category and medal success were assigned to the competition entry for the new respective age group, and as such any relative change in bodyweight category and/or medalist status with age group could be determined. As per the youth sample, multiple appearances in a particular age group were reduced to a single appearance by selecting the highest ranked entry, followed by the highest bodyweight classification in the case of tied competition rank.

In order to control for any potential differential effects of maturation, such as changes in bodyweight on relative competition performance, athletes within the retained sample were grouped by their relative change in bodyweight classification and medal success, such that athletes in a given bodyweight classification who did not change bodyweight category or medal success between age groups were differentiated from those that did. This also allowed for a more nuanced examination of the RAE on the transitioning pathway between age groups and bodyweight classification. As such, a total of 53 subsamples progressed through from entry (youth) to senior, each of which represented a unique combination of relative change in bodyweight classification and medal success between age groups.

Data Analysis

In order to assess the influence of the RAE on the longitudinal retention of youth weightlifting athletes, the distribution of retention rates across birth quartiles within each subsample were analyzed using chi^2 goodness of fit tests. Retention rates for each birth quarter within each subsample was determined by dividing the total number of athletes retained within the birth quarter by the total number of youth athletes in the respective birth quarter and bodyweight category.

Based on the rationale provided by (Delorme et al., 2010) when assessing dropout in French male soccer players, goodness of fit tests were performed by comparing the observed retention rates against a theoretical distribution that is weighted by the distribution in the corresponding youth sample. This enabled the observation of retention rates to be compared against a distribution that would be representative of the sample in question, as opposed to a theoretical null distribution, which could underreport the prevalence of the RAE when assessing longitudinal retention (Delorme et al., 2010).

Results

We wanted to understand the relationship between athlete birth quarter and retention throughout the pathway, as a function of transitions between bodyweight categories and any changes in medal success. Therefore, athletes were categorized based on the characteristics of their individual pathway. This includes athletes maintaining or changing bodyweight categories (same weight vs weight change), athletes showing emerging versus disappearing medal success (late bloomers vs lost promise), and athletes consistently achieving or not achieving medal success (safe bets vs predictable underperformers).

Safe Bets and Predictable Underperformers (Same Weight); i.e., Athletes Who Maintained Weight Category Type and Medal Success

Table 5 (p. 358) shows the distribution of the number of athletes retained in each pathway that maintained bodyweight classification and medal success by birth quarter, along with respective chi^{2}analysis. The delta values show the difference between the observed and expected number that is based on the respective underlying retention rates. For female athletes, results show disproportionate birthdate distributions in the retention of athletes in the middleweight medalist to middleweight medalist ($X^2 = 31.21$, $p < 0.001$) and heavyweight medalist to heavyweight medalist ($X^2 = 16.01$, $p < 0.001$) pathways. Moreover, results show that proportionately more athletes born in Q4 were retained in the middleweight and heavyweight medalist pathways than those born in Q1. For males, disproportionate birthdate distributions were observed in the middleweight medalist to middleweight medalist ($X^2 = 32.42$, $p < 0.001$), heavyweight medalist to heavyweight medalist ($X^2 = 14.24$, $p < 0.01$), lightweight non-medalist to lightweight non-medalist ($X^2 = 12.85$, $p < 0.01$), middleweight non-medalist to middleweight non-medalist ($X^2 = 14.15$, $p < 0.01$), and heavyweight non-medalist to heavyweight non-medalist pathways ($X^2 = 14.79$, $p < 0.01$). In these pathways, a higher proportion of athletes born in the later quartiles than in the early quartiles were retained. It is interesting to note the lack of retention effects in the lightweight medalist pathway, which is somewhat consistent with the interaction reported in Study 1.

Lost Promise or Late Bloomers (Same Weight); i.e., Athletes Who Maintained Weight Category but Changed Medal Status

The data reported in Table 6 (p. 359) represent the distribution by birth quarter of athletes that maintained bodyweight category but changed medal status between youth and senior. This includes both athletes that transitioned from being medalists at youth to failing to medal in a senior competition (i.e., lost promise), as well as athletes who were not medalists at youth but went on to win a medal at senior level (i.e., late bloomers). Results show disproportionate distributions in the female lightweight medalist to lightweight non-medalist pathway ($X^2 = 10.78$, $p < 0.05$), the female heavyweight medalist to heavyweight non-medalist pathway ($X^2 = 46.63$, $p < 0.001$), the male heavyweight medalist to heavyweight non-medalist pathway ($X^2 = 12.78$, $p < 0.01$), and the male lightweight non-medalist to lightweight medalist pathway ($X^2 = 12.48$, $p < 0.01$). All disproportionate distributions show a higher proportion of Q4 athletes retained as the pathway progresses and an increased drop-out from Q1 athletes. Interestingly, the increased Q4 retention and Q1 dropout from non-medalists to medalists occurred only in the male lightweight category. All other pathways reported did not demonstrate significant distribution asymmetries ($p > 0.05$).

Safe Bets and Predicted Underperformance (Weight Change); i.e., Athletes Who Changed Weight Category Type but Maintained Medal Status

Table 7 (p. 360-361) shows the distribution by birth quarter and chi^{2}statistics for athletes that changed weight category but maintained medal status. Results show that distribution asymmetries in the female middleweight non-medalist to lightweight non-medalist pathway ($X^2 = 9.13$, $p < 0.05$), the male lightweight medalists to middleweight medalists ($X^2 = 16.27$, $p < 0.001$) and lightweight non-medalist to middleweight non-medalist ($X^2 = 13.83$, $p <$

0.01) pathways. In all pathways, over-representation was observed for athletes retained who were born in Q4.

Lost Promise or Late Bloomers (Weight Change); i.e., Athletes Who Changed Weight Category Type and Medalist Status

Lastly, the data shown in Table 8 (p. 362-363) show the distribution by birth quarter in the athletes that changed both bodyweight category type and medal status in the pathway from youth to senior. Results show disproportionate birthdate distributions in the female heavyweight medalist to middleweight non-medalist ($X^2 = 14.55$, $p < 0.01$), middleweight non-medalists to lightweight medalist ($X^2 = 11.35$, $p < 0.01$), heavyweight non-medalist to middleweight medalist ($X^2 = 13.09$, $p < 0.01$), and the male lightweight medalist to middleweight non-medalist ($X^2 = 7.96$, $p < 0.05$) pathways.

Discussion

To facilitate understanding of retention mechanisms underlying RAE findings in Study 1, Study 2 sought to investigate athlete retention as a function of birth quarter throughout the pathway. This was dependent on transitional characteristics of an athlete's individual pathway from youth to senior i.e., dependent on whether or not an athlete maintained or changed bodyweight category and subsequent medal success. These data provide valuable talent identification and selection information for practitioners regarding the likelihood of Q1 athletes selected at youth level (based on maturational advantages), maintaining their success at later stages of the pathway. Furthermore, findings help us to understand what happens to Q4 athletes who remain in the system and whether they have the potential to become late bloomers. This has important implications for selection and development. While literature suggests educating coaching staff on RAE may not be sufficient in reducing or preventing RAE (Mann & van Ginneken, 2017), one option might be pushing selection periods back into later stages of athletes' development. This would have the benefit of reducing talent wastage but warrants further investigation. Similarly, Webdale et al. (2020) propose that this type of approach may also support physiological and psychological development of athletes as well as providing a prolonged experience prior to selection periods. However, they also identify some potential problems in that this may not be supported by parents and coaches (both integral to the success of junior development programs), may impair early experiences for some athletes and could have consequences for later success at international levels.

While previous literature predicts increased selection (and thus, retention) of Q1 athletes, (i.e., the RAE; Barnsley et al., 1985), overall findings revealed a higher proportion of drop-out from Q1 athletes compared to Q4 athletes from youth to senior. This was supported by higher proportions of Q4 athletes retained in the pathway. This inconsistency is likely due to investigating athlete retention over time where previous research typically adopts cross-sectional approaches (see Cobley et al., 2009 for a review). This finding is also consistent with data observing reduced prevalence of RAE over time (e.g., Faber et al., 2019). Furthermore, and more interestingly, we see a higher proportion of Q4 athletes transitioning from being a non-medalist to a medalist compared with Q1 athletes as they progress from youth to senior. It is important to understand the mechanisms which allow Q4 athletes to achieve this.

In terms of medal success specifically, we see a higher proportion of male and female Q4 athletes in the middle and heavyweight categories maintaining bodyweight category as well as medal success; i.e., our "safe bets." Lightweight categories seem less vulnerable to the RAE (possibly because Q1 athletes exhibiting physical prowess as a result of biological maturation tend to end up in higher weight categories at youth level), and thus it may be that as a result, birth quarters have less influence on athlete retention in this weight category. Alternatively, this may be a result of Q1 athletes dropping out, as well as Q1 athletes transitioning down from middleweight to lightweight categories as they progress through the developmental stages. Similarly, we see a higher proportion of Q4 athletes moving from lightweight to middleweight but retaining medal success. It is possible males are more able to sustain success when transitioning into higher weight categories compared to females. For those athletes who emerge as medalists only at the senior level, there is an increased prevalence of Q4 athletes achieving this for lightweight categories only (females verging on significance at 0.067). Finally, we see a similar prevalence of Q4 athletes who transition down weight categories and achieve medal success (females moving from middle to lightweight categories and males moving from heavy to middleweight categories).

Study 3

This increased prevalence of Q4 athletes emerging as medalists only at senior level, may be a consequence of a “rocky road” or increased psychological determinants of expertise for relatively younger athletes (Collins & MacNamara, 2012; Hardy et al., 2017; Jones et al., 2018; Rees et al., 2016). To date, these potential psychological underpinnings of RAE have been hypothetical in nature and yet to be tested. Study 3 sought to investigate RAE in the context of key psychological characteristics, integral to expertise.

Methods

Participants and Procedure

As part of a separate investigation into the longitudinal development of junior weightlifting athletes, 44 youth and junior weightlifting athletes (n males = 30, *n* females = 14, mean age ± *SD* = 15.6 ± 1.9) completed a battery of tests. The sample contained a distribution of 54% middleweight (*N* = 22), 34% lightweight (*N* = 14), and 12% heavyweight athletes (*N* = 5). All lifters were UK based. Athletes completed a battery of psychometric tests which evaluated a range of psychosocial attributes. These attributes included behaviors and attitudes toward training and competition such as achievement goal motivation, mastery and outcome focus, commitment to training, total preparation for competition, counterphobic attitude, and the relative importance of weightlifting in relation to other life choices. In addition, the psychometric battery also included trait personality measurements which have also been shown to discriminate super elite from elite performance (Hardy et al., 2017). These personality traits were perfectionism, ruthlessness and selfishness, obsessiveness, and the big five personality traits: conscientiousness, extraversion, emotional stability, agreeableness, and openness to experience.

The psychometric battery consisted of 110 items, which were a formulation of existing psychometric inventories. Specifically, the battery consisted of the 2 x 2 achievement goal questionnaire for sport (AGQ-S) (Conroy et al., 2003), an early iteration of an athlete psychological survey (based on findings from Hardy et al., 2017), the importance of others in the self (Aron et al., 1992), the ten item personality inventory (TIPI; Gosling et al., 2003), the sport multidimensional perfectionism scale-2 (Sport-MPS-2; Gotwals & Dunn, 2009), the passion scale (Vallerand et al., 2003), and an adapted version of the Yale-brown obsessive-compulsive scale (Goodman et al., 1989), which was adapted to suit athlete obsessive thoughts and behaviors toward weightlifting.

In order to investigate the relationship between RAE and the aforementioned psychosocial attributes, the sample of athletes was grouped into half-year quartiles based on their month of birth (H1 vs H2), such that the athletes born between January 1 and June 30 were assigned to the first half-year quantile (H1), while the athletes born between July 1 and December 31 were assigned to the second half-year quartile (H2). This resulted in a H1 sample size of 19 (14 males, 5 females, mean ± *SD* = 15.5 ± 1.9), and a H2 sample size of 25 (16 males, 9 females, mean ± *SD* age = 15.7 ± 1.9).

Data Analysis

A Bayesian pattern recognition analysis was performed on the dataset to determine the subset of psychometric items that best classified birth-group membership. This analysis followed a two-part process, both of which made use of machine learning algorithms specifically designed for classification problems. The first part, termed feature selection, is a process that examines the relative importance of each item based on its respective predictive validity. Depending on the algorithm used, each item in the dataset was either ranked by order of predictive power or was assigned a numerical value based on the number of iterations the algorithm had identified its importance. For this process, four separate algorithms were used to perform feature selection; namely the correlation attribute evaluator (CAE), the relief F attribute evaluator (Kira & Rendell, 1992), the support vector machine attribute evaluator (cf. Guyon et al., 2002), and the correlation-based feature selection (CFS; Hall, 1999) subset evaluator. As each algorithm used a slightly different logic process, and thus varied somewhat in the items they selected, the items that were ranked in the top 40th percentile of selected items across all four of the feature selection algorithms were ultimately selected for the next stage in the analysis (also see Jones et al., 2019; Jones et al., 2020).

The second part of the process, classification, utilized classification algorithms to assign each participant with an expected group membership based on their respective scores on the selected items. For this step, four commonly used classification algorithms were used, namely the naïve Bayes (cf. John & Langley, 1995), J48 decision tree (cf. Quinlan, 1993), support vector machine (cf. Platt, 1999) and K-nearest neighbors (Aha et al., 1991). This classification process was performed iteratively using a leave-one-out cross-validation procedure in order to minimize overfitting the findings to the data and thus preserving the generalizability of the resulting model. The classification rate (i.e., the number of athletes correctly classified versus the total sample size) for each algorithm reported in this study is therefore an average score for all of the iterations performed. The pattern recognition analysis was performed using the rWeka package in R (Hornik et al., 2009), which is a R interface for the WEKA machine learning statistical software package (Witten et al., 2011).

Results

The selected features and thus the resulting model are presented in Table 9 (p. 364). A total of four constructs were selected from a potential of 26, namely the following: mastery approach, concern over mistakes, emotional stability, and openness to experience. Table 9 shows the group means for each item by each birthdate quantile. Athletes born in the first half of the year generally scored higher on emotional stability than those born in the second half of the year, while the inverse relationship was true for mastery approach, concern over mistakes, and openness to experience. This relationship is also depicted in Figure 2.

Table 10 (p. 364) shows the results for the classification. Overall, the resulting model was able to differentiate athlete birth halves successfully with a 58.5% accuracy. The discrepancy between the sensitivity and specificity parameters (0.682 vs 0.473) also suggests that this model tended to classify athletes correctly in the second half of the year more successfully than athletes in the first. An average area under the curve of 0.57, which is generally used as measure of model efficacy, suggests that this model is generally a weak predictor of the relative age effect (moderate to strong models tend to range between 0.8 and 1; Obuchowski et al., 2004), although the model was still able to perform better than a completely naïve model (i.e., that which will return a 50% success rate). However, when the same models were used to classify just the Q1 and Q4 sample, the model performance markedly improved (see parenthesized values in Table 10). An area under the ROC curve of 0.756 for the Q1 vs Q4 sample suggests that the model was able to differentiate Q1 versus Q4 athletes with relatively better performance (76%).

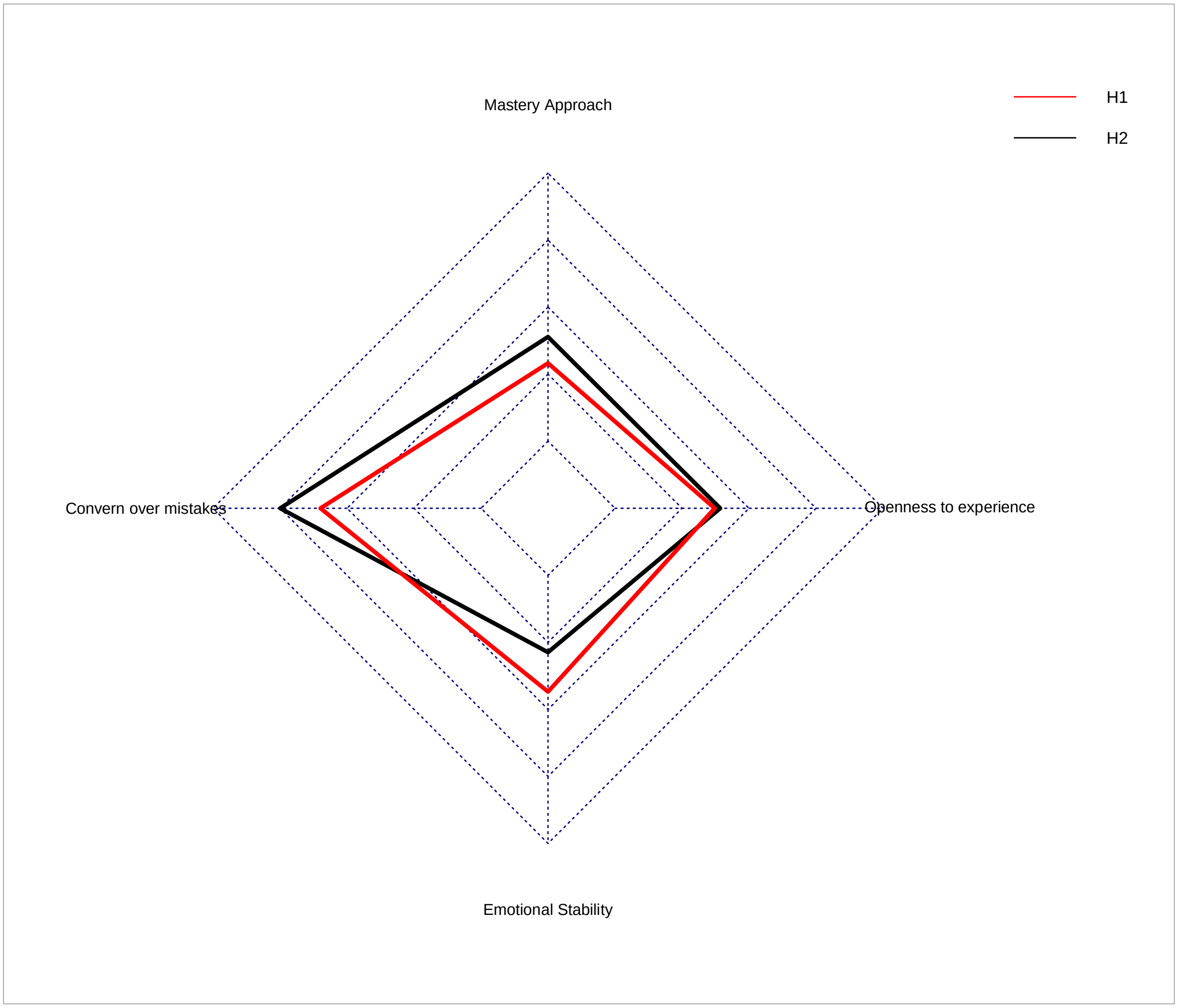

Figure 2. Radar plot depicting the relationships between birth halves and each of the four attributes in the model.

Discussion

Study 3 set out to determine if the RAE could account for differences in the psychosocial profiles of youth and junior weightlifting athletes. It was found that the RAE could be accounted for by a combination of motivational and personality characteristics, namely mastery approach, concern over mistakes, emotional stability, and openness to experience. Each construct will be briefly discussed in the context of the RAE.

Mastery approach is an achievement motivation construct, which describes the attainment of competence that is based on becoming the best version of oneself, as opposed to competence that is based on the self in comparison with others (Roberts et al., 2012). Individuals who are mastery-approach motivated tend to strive to be better than their last performance, and generally show traits of adaptive achievement motivation, such as increased intrinsic motivation (Elliot & Harackiewicz, 1996) and absorption in the task (Cury et al., 2002). Mastery approach is also seen in the achievement motivation literature to be a distinctly different construct from performance approach (Conroy et al., 2003), the latter of which describes motivation toward the attainment of competence that is based on social comparisons with peers. In the context of the current study, this would seem to suggest that the relatively younger athletes tended to report higher scores for mastery approach perhaps as an indirect consequence of being relatively younger. Moreover, perhaps being relatively younger led these athletes to be more focused on aspects of their own performance which require improvement, as opposed to being driven to outperform others in tasks in which they may have been biologically or psychologically disadvantaged from the outset. Furthermore, given the association between mastery approach and intrinsic motivation (Elliot & Harackiewicz, 1996), this form of motivation could have also encouraged these relatively younger athletes to stay in the sport until the physical disadvantages were no longer apparent.

Concern over mistakes describes a maladaptive form of perfectionism, which describes a tendency to react negatively to one's own performance (Dunn et al., 2006). Athletes exhibiting concern over mistakes tend to exhibit higher forms of cognitive and somatic anxiety (Hall et al., 1998), which could also account for the lower emotional stability observed in the relatively younger athletes in the current study. This concern over mistakes could have also occurred as a result of reactions to one's own performance being confounded with the biological disadvantages that a part of being relatively younger. Moreover, the potential long-term benefits of overcoming these concerns over mistakes, especially when combined with adopting a mastery approach motivation, could have led to more resilience in these athletes. This proposition would indeed require further empirical support.

Emotional stability describes an individual's tendency to remain stable and balanced in a wide variety of situations (Thomas et al., 1999). Both emotional stability and openness to experience form part of the big five personality traits. This trait could have perhaps emerged as a result of psychological maturation in the relatively older athletes. It is also worthy of note that the two items in the questionnaire that targeted this construct were "I see myself as anxious, easily upset" and "I see myself as calm, emotionally stable." As the athletes in the questionnaire were asked about these questions in relation to their weightlifting performance, it could be very likely that the relatively older athletes could have answered these questions in relation to scenarios that were as a result of their psychological maturation, as well as being calmer in competitive scenarios in which they were biologically advantaged.

Openness to experience refers to the breadth and complexity of one's mental and experiential life (Costa et al., 1991). Openness to experience has also been associated with sensation seeking, and the tendency to seek varied experiences, which are often accompanied by heightened risk taking (e.g., Tok, 2011). Given that weightlifting is a sport that offers quite intense emotional experiences during competition (i.e., the intense emotion associated with failing or succeeding a lift), the relatively younger athletes could have been attracted to the sport for the purposes of sensation seeking. This could also lead to increased attraction to the sport, beyond the obvious attraction of winning. This may not be as prevalent in the relatively older athletes, for whom attraction to the sport may be based on their physical advantages of being relatively older.

General Discussion

The aim of the present series of studies was to test the relationship between RAE, gender, and bodyweight classification over progressing developmental stages of an elite weightlifting pathway. Furthermore, we wanted to address this in the context of performance success over the course of the pathway, athlete retention between different developmental stages of the pathway, and any underlying psychological determinants of expertise. The multidisciplinary nature of this approach was in line with a developmental systems model (Wattie et al., 2015), proposing individual, task and environmental constraints in influencing RAE. The longitudinal design of the present studies also allowed us to consider the dynamic nature of these constraints during the developmental pathway. Overall findings revealed a typical RAE across all age groups and weight categories with the exception of female junior heavyweight and lightweight categories. Retention data suggest that despite this RAE, a higher relative proportion of Q4 athletes were retained in the pathway from youth to senior. Furthermore, we see a higher proportion of Q4 athletes transitioning from being a non-medalist to a medalist compared with Q1 athletes as they move through the pathway. These findings have several implications for coaches and practitioners within the pathway.

Researchers have previously hypothesised an elimination of RAE when environmental constraints in the form of weight categories are present (see Albuquerque et al., 2016). The present findings highlight the robustness of the RAE despite these weight categories, which arguably limit the extent to which athletes of greater physical mass are competing directly against those of inferior mass. This supports the notion that mechanisms underpinning RAE are not solely biological in nature and are more likely a combination of bio-psycho-social mechanisms. In line with this, Schorer et al. (2009) found no difference in physical size between relatively older and younger junior handball players by 13-15 years, supporting the notion that mechanisms underpinning RAE occur early in an athlete's development.

A consequence of the cross-sectional approaches largely adopted throughout the RAE literature is limited understanding regarding an athlete's journey within a sporting system. The current findings tell us that it is the relatively younger athletes that are more likely to be retained from youth through to senior. It is also these particular athletes that are more likely to become late bloomers and medal at senior level. We propose that one reason for this is Q4 athletes exhibiting higher levels of some important psychological determinants of expertise. To the authors' knowledge, this is the first study to test this in the context of RAE. Results identified the following attributes as being integral to this process: mastery approach, concern over mistakes, emotional stability, and openness to experience. These characteristics have been recognized in the literature as being integral to expertise development (Hardy et al., 2017).

Considering these findings in the context of social mechanisms that have been proposed to account for RAE findings, it stands to reason that Pygmalion effects may be relevant when explaining the relationship between RAEs in weightlifting, performance success, psychological development, and drop-out. More specifically, Pygmalion effects are a logical contributory factor in the overrepresentation of Q1 athletes in weightlifting. This may be a result of coaches holding greater expectations of relatively older athletes compared to their younger counterparts. This can lead to favorable coach behaviors toward these athletes such as more individualized coaching, increased support from coaching staff at competitions etc. However, this explains only an increased "presence" within the system for Q1 athletes and does not seem to coincide with subsequent performance. The current authors hypothesize that consequent coach behaviors toward relatively younger athletes; e.g., reduced individual coaching or support as a result of this time and energy being directly more favorably toward their older counterparts, may paradoxically result in Q4 athletes developing some important psychological determinants for success and progression through a system such as mastery. Conversely, once in the system Q1 athletes seem less likely to develop these characteristics and may try to rely on their status as "being older" to succeed (or indeed expect to succeed due to the aforementioned Pygmalion effect and a subsequent Galatea effect). Once maturational biases are no longer in the athletes' favor, the expectation to succeed may be present but no longer achievable, and they may drop out as a result.

Practical recommendations of RAE remain largely under debate and warrant further scrutiny. Indeed, Webdale et al.'s (2020) review of "proposed solutions," indicates that while many exist, few have actually been tested in practical settings. The authors also identify a number of problems associated with particular solutions, which include difficulties implementing, social disadvantages, health risks, and limiting success on international platforms. It is widely accepted that practitioners should caution against selection criteria biased toward relatively older athletes (Hardy et al., 2017). What we are less sure of is the longer-term effects of methods such as quota systems (Barnsley and Thompson, 1988), rotating cut-off dates (Hurley et al., 2001), or bio-banding techniques (Cumming et al., 2017). These policy/social actions may also have unforeseen consequences by negating the development of psychological characteristics fostered when relatively younger athletes train and compete against their relatively older counterparts. In line with this, we would strongly recommend practitioners include psychometric testing within talent identification models. This will help identify athletes who may be less likely to stand out based on physical attributes, but who may possess important psychological characteristics that may increase their chances of becoming late bloomers. This can also be used as a development tool for athletes who may otherwise drop out before transitioning to senior. Ultimately aiding retention of Q1 athletes that may not otherwise fulfil early promise.

It is important to note that this body of work was not without limitations, some of which may be valuable in prompting future research avenues. For Study 1, we adopted cross-sectional data, and while this enabled us to explore a much larger sample size, arguably a necessity when employing chi^2 analyses (McHugh, 2013), it did not facilitate exploration of athlete development via longitudinal effects. Similarly, it could be argued that over the 20-year time-period adopted, task, individual, and environmental constraints may well have shifted over time due to systemic changes within the sport[1]. Methodological design for Study 2 enabled us to track athlete development over the course of a system, but emphasis was on understanding athlete retention, and subsequently performance success was an independent as opposed to dependent variable.

Finally, while Study 3 allowed us to explore psychological characteristics more directly, and as a function of birth month, this meant that data were limited with regard to sample size. However, to account for this we have reported performance diagnostics across four different machine learning algorithms (it is typical in machine learning research to report only one) avoiding the potential for "overfitting" (to thus preserve generalizability) by administering a "leave one out" cross validation procedure. Furthermore, the four psychosocial features within the final model appeared in all four of the separate machine learning classification methods offering greatly increased confidence in their predictive weighting. While we are confident in these findings but support a degree of caution, sample size did limit the extent to which we were able to explore any gender effects, an avenue of value for future research direction, especially given the gender nuances revealed within Study 1.

In summary, the present series of studies provides a comprehensive test of developmental systems model (Wattie et al., 2015) in weightlifting, and reinforces the notion of considering RAE in the context of individual, task, and environmental constraints. On the basis of this model, two athletes born on the same day will have very different developmental experiences. We would thus caution against practitioners applying a "one-size-fits-all" approach to athlete selection and development.

Endnote

1. As the data span a large time-period of international events, data were also explored over incremental 5-year periods (e.g., 1998-2002; 2003-2007; 2008-2012; 2013-2017). The rationale here was to determine whether RAE findings change as a function of time, thus reflecting changes in constraints influencing the RAE phenomenon. Data analysis across these time frames was largely aligned with the overall data analysis reported in the main body of the text. For reasons of brevity, we report only findings associated with the complete data set.

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Authors' Declaration

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

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

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

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Table 1. Breakdown of bodyweight category types

		Category Type		
Sex	Age Group	Lightweight	Middleweight	Heavyweight
Female	Youth	44kg, 48kg	53kg, 58kg, 63kg	69kg, 69kg+
	Junior & Senior	48kg, 53kg	58kg, 63kg, 69kg	75kg, 75kg+
Male	Youth	50kg, 56kg	62kg, 69kg, 77kg	85kg, 85kg+
	Junior & Senior	56kg, 62kg	69kg, 77kg, 85kg	94kg, 105kg, 105kg+

Table 2. Birthdate distributions, chi^2 analyses, and odds ratios with 95% confidence intervals arranged by Sex, Age Group, and Bodyweight Category (significance indicated in bold)

Sex	Age Group	Bodyweight Category	N	Q1 (%)	Q2 (%)	Q3 (%)	Q4 (%)	χ^2	*p*	OR (CI) Q1vQ4	OR (CI) Q2vQ4	OR (CI) Q3vQ4	OR (CI) H1vH2
Female	Youth	Lightweight	311	30.23	22.83	25.08	21.86	5.21	0.157	1.38 (0.87-2.21)	1.04 (0.64-1.7)	1.13 (0.7-1.83)	1.14 (0.82-1.58)
		Middleweight	621	31.72	26.25	23.51	18.52	22.6	**<0.01**	1.7 (1.22-2.37)	1.42 (1.01-1.99)	1.27 (0.9-1.79)	1.37 (1.09-1.73)
		Heavyweight	348	30.75	26.44	23.56	19.25	9.77	**0.021**	1.59 (1.02-2.5)	1.37 (0.87-2.17)	1.22 (0.77-1.94)	1.33 (0.98-1.82)
	Junior	Lightweight	474	36.71	20.46	21.73	21.1	34.81	**<0.01**	1.74 (1.2-2.52)	0.96 (0.65-1.43)	1.03 (0.7-1.53)	1.33 (1.02-1.73)
		Middleweight	755	35.5	21.19	23.58	19.74	46.64	**<0.01**	1.8 (1.34-2.42)	1.07 (0.79-1.47)	1.19 (0.87-1.62)	1.31 (1.07-1.62)
		Heavyweight	444	28.15	23.87	22.3	25.68	3.37	0.338	1.1 (0.75-1.61)	0.93 (0.63-1.37)	0.87 (0.59-1.29)	1.08 (0.83-1.42)
	Senior	Lightweight	500	33.2	20.6	22.8	23.4	18.8	**<0.01**	1.42 (0.99-2.03)	0.88 (0.6-1.29)	0.97 (0.67-1.42)	1.16 (0.9-1.5)
		Middleweight	908	30.18	24.01	22.8	23.02	13.28	**<0.01**	1.31 (1.01-1.71)	1.04 (0.79-1.37)	0.99 (0.75-1.3)	1.18 (0.98-1.43)
		Heavyweight	505	31.29	25.35	22.57	20.79	12.77	**<0.01**	1.49 (1.04-2.15)	1.22 (0.84-1.77)	1.09 (0.74-1.59)	1.3 (1.01-1.68)
Male	Youth	Lightweight	458	31.66	22.27	25.55	20.52	13.21	**<0.01**	1.54 (1.05-2.26)	1.08 (0.72-1.6)	1.24 (0.84-1.84)	1.17 (0.89-1.52)
		Middleweight	922	36.12	25.27	21.15	17.46	72.03	**<0.01**	2.07 (1.58-2.71)	1.44 (1.09-1.91)	1.21 (0.91-1.61)	1.59 (1.31-1.92)
		Heavyweight	660	36.52	25.91	22.42	15.15	62.58	**<0.01**	2.41 (1.73-3.35)	1.71 (1.22-2.41)	1.48 (1.05-2.09)	1.66 (1.33-2.08)
	Junior	Lightweight	639	33.96	21.28	25.2	19.56	31.62	**<0.01**	1.73 (1.26-2.4)	1.09 (0.77-1.53)	1.28 (0.92-1.79)	1.24 (0.99-1.55)
		Middleweight	1238	33.93	22.94	23.1	20.03	55.56	**<0.01**	1.69 (1.35-2.13)	1.14 (0.9-1.45)	1.15 (0.91-1.46)	1.32 (1.12-1.55)
		Heavyweight	1032	33.82	22.67	25.29	18.22	53.36	**<0.01**	1.86 (1.44-2.4)	1.24 (0.95-1.63)	1.39 (1.07-1.81)	1.3 (1.09-1.55)
	Senior	Lightweight	601	38.6	20.8	19.97	20.63	59.4	**<0.01**	1.86 (1.34-2.58)	1.01 (0.71-1.43)	0.97 (0.68-1.38)	1.46 (1.15-1.84)
		Middleweight	1307	34.28	20.28	23.95	21.5	63.65	**<0.01**	1.59 (1.28-1.99)	0.94 (0.75-1.19)	1.11 (0.88-1.4)	1.2 (1.03-1.41)
		Heavyweight	1131	33.95	21.31	24.14	20.6	51.51	**<0.01**	1.65 (1.3-2.09)	1.03 (0.8-1.33)	1.17 (0.91-1.5)	1.24 (1.05-1.46)

N = sample size, Q = birthdate quartile, OR = odds ratio, H = half year (by 6 months)

Table 3. Multiple logistic regression on Q1 vs Q4 membership for female weightlifting athletes (significance indicated in bold).

Term	Log odds Estimate (Standard Error)	*p*	Odds Ratio
Intercept	0.36 (0.24)	0.13	1.43 (0.9-2.3)
Junior	0.13 (0.29)	0.65	1.14 (0.64-2.02)
Senior	0.11 (0.3)	0.72	1.11 (0.62-1.99)
Middleweight	-0.04 (0.28)	0.88	0.96 (0.54-1.67)
Heavyweight	-0.1 (0.31)	0.76	0.91 (0.49-1.68)
Medalist	-0.07 (0.32)	0.84	0.94 (0.5-1.75)
Junior x Middleweight	0.3 (0.36)	0.41	1.35 (0.66-2.75)
Senior x Middleweight	-0.03 (0.36)	0.93	0.97 (0.48-1.95)
Junior x Heavyweight	-0.24 (0.41)	0.55	0.78 (0.35-1.75)
Senior x Heavyweight	0.1 (0.4)	0.80	1.11 (0.51-2.43)
Junior x Medalist	0.2 (0.41)	0.63	1.22 (0.55-2.71)
Senior x Medalist	-0.16 (0.4)	0.70	0.85 (0.39-1.88)
Middleweight x Medalist	0.56 (0.4)	0.16	1.75 (0.8-3.83)
Heavyweight x Medalist	0.56 (0.45)	0.22	1.74 (0.72-4.26)
Junior x Middleweight x Medalist	-1.03 (0.52)	**<0.05**	0.36 (0.13-0.98)
Senior x Middleweight x Medalist	-0.63 (0.5)	0.21	0.53 (0.2-1.42)
Junior x Heavyweight x Medalist	-0.8 (0.58)	0.17	0.45 (0.14-1.4)
Senior x Heavyweight x Medalist	-0.46 (0.57)	0.42	0.63 (0.2-1.92)

** Significant at the 95% confidence level*

Table 4. Multiple logistic regression on Q1 vs Q4 membership in male weightlifting athletes (significance indicated in bold).

Term	Log odds Estimate (Standard Error)	*p*	Odds Ratio
Intercept	0.67 (0.18)	**<0.01**	1.96 (1.38-2.81)
Junior	-0.07 (0.23)	0.77	0.93 (0.59-1.48)
Senior	-0.04 (0.23)	0.85	0.96 (0.61-1.51)
Middleweight	0.03 (0.22)	0.90	1.03 (0.67-1.57)
Heavyweight	0.16 (0.24)	0.51	1.17 (0.73-1.89)
Medalist	-0.54 (0.27)	**<0.05**	0.59 (0.35-0.99)
Junior x Middleweight	-0.12 (0.28)	0.67	0.89 (0.51-1.54)
Senior x Middleweight	-0.04 (0.28)	0.90	0.96 (0.56-1.67)
Junior x Heavyweight	-0.24 (0.31)	0.44	0.79 (0.43-1.45)
Senior x Heavyweight	-0.25 (0.3)	0.41	0.78 (0.43-1.41)
Junior x Medalist	0.41 (0.35)	0.24	1.51 (0.76-3.01)
Senior x Medalist	0.53 (0.35)	0.13	1.7 (0.86-3.38)
Middleweight x Medalist	0.62 (0.34)	0.07	1.85 (0.96-3.59)
Heavyweight x Medalist	0.64 (0.36)	0.08	1.89 (0.94-3.83)
Junior x Middleweight x Medalist	-0.44 (0.44)	0.32	0.64 (0.27-1.52)
Senior x Middleweight x Medalist	-1.02 (0.43)	**0.02**	0.36 (0.15-0.84)
Junior x Heavyweight x Medalist	-0.29 (0.46)	0.54	0.75 (0.3-1.86)
Senior x Heavyweight x Medalist	-0.72 (0.46)	0.11	0.48 (0.2-1.18)

Table 5. Number of retained athletes who maintained weight category type and medalist status by birth quarter (χ^2 significance indicated in bold).

Sex	Pathway (Youth to Senior)	Q1	Q2	Q3	Q4	Total	χ^2	p
	Medalists to Medalists							
Female	Lightweight to Lightweight	10	4	7	6	27	6.81	0.078
	(Δ)	(-1)	(-3)	(+2)	(0)			
	Middleweight to Middleweight	10	22	13	15	60	31.21	**<0.001**
	(Δ)	(-19)	(+9)	(0)	(+6)			
	Heavyweight to Heavyweight	5	13	11	7	36	16.01	**0.001**
	(Δ)	(-5)	(+1)	(+1)	(+3)			
Male	Lightweight to Lightweight	11	5	6	9	31	0.72	0.869
	(Δ)	(-2)	(0)	(0)	(0)			
	Middleweight to Middleweight	16	10	15	16	57	32.42	**<0.001**
	(Δ)	(-17)	(-6)	(+4)	(+9)			
	Heavyweight to Heavyweight	11	11	9	8	39	14.24	**0.003**
	(Δ)	(-15)	(+1)	(+2)	(+4)			
	Non-Medalists to Non-Medalists							
Female	Lightweight to Lightweight	5	1	4	1	11	4.58	0.205
	(Δ)	(+1)	(-1)	(+1)	(-1)			
	Middleweight to Middleweight	13	11	6	10	40	2.83	0.419
	(Δ)	(+1)	(-1)	(-3)	(+3)			
	Heavyweight to Heavyweight	11	3	7	8	29	6.16	0.104
	(Δ)	(+1)	(-3)	(+2)	(+1)			
Male	Lightweight to Lightweight	5	3	12	6	26	12.85	**0.005**
	(Δ)	(-6)	(-3)	(+4)	(+3)			
	Middleweight to Middleweight	17	5	22	11	55	14.15	**0.003**
	(Δ)	(-10)	(-8)	(+11)	(+3)			
	Heavyweight to Heavyweight	2	12	9	5	28	14.79	**0.002**
	(Δ)	(-12)	(+3)	(+2)	(+2)			

Note: Δ represents the difference between the observed value and the expected theoretical value.

Table 6. Number of retained athletes who retained weight category status but changed medalist status by birth quarter (χ^2 significance indicated in bold).

Sex	Pathway (Youth to Senior)	Q1	Q2	Q3	Q4	Total	χ^2	*p*
	Medalist to Non-Medalist							
Female	Lightweight to Lightweight	3	6	4	6	19	10.78	**0.013**
	(Δ)	(-5)	(+1)	0	(+2)			
	Middleweight to Middleweight	9	7	8	5	29	3.5	0.32
	(Δ)	(-5)	(+1)	(+2)	(+1)			
	Heavyweight to Heavyweight	3	5	2	7	17	46.63	**<0.001**
	(Δ)	(-2)	(-1)	(-3)	(+5)			
Male	Lightweight to Lightweight	9	4	7	6	26	3.94	0.268
	(Δ)	(-2)	0	(+2)	(-1)			
	Middleweight to Middleweight	22	10	14	7	53	6.85	0.077
	(Δ)	(-6)	(-3)	(+5)	(+1)			
	Heavyweight to Heavyweight	13	13	7	8	41	12.78	**0.005**
	(Δ)	(-13)	(+3)	0	(+4)			
	Non-Medalist to Medalist							
Female	Lightweight to Lightweight	3	2	5	4	14	7.16	0.067
	(Δ)	(-2)	(-1)	(+1)	(+2)			
	Middleweight to Middleweight	2	4	5	3	14	3.04	0.385
	(Δ)	(-2)	0	(+2)	0			
	Heavyweight to Heavyweight	5	3	3	2	13	1.16	0.763
	(Δ)	(+1)	0	(+1)	(-1)			
Male	Lightweight to Lightweight	2	3	6	5	16	12.48	0.006
	(Δ)	(-5)	(-1)	(+1)	(+3)			
	Middleweight to Middleweight	13	5	0	7	25	5.16	0.161
	(Δ)	(+1)	(-1)	0	(+3)			
	Heavyweight to Heavyweight	3	3	5	2	13	4.57	0.206
	(Δ)	(-3)	(-1)	(+2)	(+1)			

Note: Δ represents the difference between the observed value and the expected theoretical value

Table 7. Number of retained athletes who maintained medalist status but changed weight category type by birth quarter (χ^2 significance indicated in bold).

Sex	Pathway (Youth to Senior)	Q1	Q2	Q3	Q4	Total	χ^2	p
	Medalists to Medalists							
Female	Lightweight to Middleweight	1	0	1	1	3	3.72	0.293
	(Δ)	0	0	0	0			
	Middleweight to Lightweight	7	3	3	2	15	0.03	0.999
	(Δ)	0	0	0	0			
	Middleweight to Heavyweight	1	0	0	0	1	2.04	0.564
	(Δ)	(+1)	0	0	0			
	Heavyweight to Middleweight	3	3	2	2	10	2.65	0.448
	(Δ)	0	0	(-1)	(+1)			
Male	Lightweight to Middleweight	1	0	3	2	6	16.27	**<0.001**
	(Δ)	(-2)	0	(+2)	(+1)			
	Middleweight to Lightweight	6	2	2	1	11	0.34	0.953
	(Δ)	(+1)	(-1)	0	0			
	Middleweight to Heavyweight	2	1	0	2	5	5.23	0.155
	(Δ)	(-1)	0	0	(+1)			
	Heavyweight to Middleweight	4	3	1	2	10	3.21	0.361
	(Δ)	(-2)	(+1)	(-1)	(+1)			

Note: Δ represents the difference between the observed value and the expected theoretical value

Table 7 continued on next page.

Table 7., continued. Number of retained athletes who maintained medalist status but changed weight category type by birth quarter (χ^2 significance indicated in bold).

Sex	Pathway (Youth to Senior)	Q1	Q2	Q3	Q4	Total	χ^2	*p*
	Non-Medalists to Non-Medalists							
Female	Lightweight to Middleweight	1	0	0	0	1	5.9	0.116
	(Δ)	(+1)	0	0	0			
	Middleweight to Lightweight	1	2	2	5	10	9.13	**0.028**
	(Δ)	(-2)	(-1)	0	(+3)			
	Heavyweight to Middleweight	1	2	2	0	5	6.28	0.099
	(Δ)	(-1)	(+1)	(+1)	0			
Male	Lightweight to Middleweight	0	1	0	3	4	13.83	**0.003**
	(Δ)	0	(-1)	0	(+2)			
	Middleweight to Lightweight	3	3	3	4	13	3.19	0.364
	(Δ)	(-4)	0	0	(+2)			
	Middleweight to Heavyweight	2	1	1	0	4	0.55	0.908
	(Δ)	0	0	0	0			
	Heavyweight to Middleweight	2	1	3	2	8	6.51	0.089
	(Δ)	(-2)	(-2)	(+1)	(+1)			

Note: Δ represents the difference between the observed value and the expected theoretical value

Table 8. Number of retained athletes who changed bodyweight category and medalist status by birth quarter (χ^2 significance indicated in bold).

Sex	Pathway (Youth to Senior)	Q1	Q2	Q3	Q4	Total	χ^2	*p*
	Medalist to Non-Medalists							
Female	Middleweight to Lightweight	5	3	3	1	12	1.04	0.791
	(Δ)	(0)	(+1)	(+1)	(-1)	12		
	Heavyweight to Lightweight	0	0	1	0	1	5.07	0.167
	(Δ)	(0)	(0)	(+1)	(0)	1		
	Heavyweight to Middleweight	1	4	2	3	10	14.55	**0.002**
	(Δ)	(-2)	(+1)	(-1)	(+2)	10		
Male	Lightweight to Middleweight	0	1	0	0	1	7.96	**0.047**
	(Δ)	(0)	(+1)	(0)	(0)	1		
	Middleweight to Lightweight	3	3	1	0	7	2.89	0.409
	(Δ)	(0)	(+1)	(0)	(0)	7		
	Heavyweight to Lightweight	1	0	0	1	2	3.69	0.297
	(Δ)	(0)	(0)	(0)	(+1)	2		
	Heavyweight to Middleweight	4	1	2	2	9	3.64	0.304
	(Δ)	(-2)	(-1)	(0)	(+1)	9		

Note: Δ represents the difference between the observed value and the expected theoretical value

Table 8 continued on next page.

Table 8., continued. Number of retained athletes who changed bodyweight category and medalist status by birth quarter (χ^2 significance indicated in bold).

Sex	Pathway (Youth to Senior)	Q1	Q2	Q3	Q4	Total	χ^2	*p*
	Non-Medalists to Medalists							
Female	Middleweight to Lightweight	1	1	2	5	9	11.35	**0.01**
	(Δ)	(-2)	(-2)	(0)	(+3)	9		
	Middleweight to Heavyweight	1	0	0	0	1	3.1	0.376
	(Δ)	(+1)	(0)	(0)	(0)	1		
	Heavyweight to Middleweight	1	0	3	0	4	13.09	**0.004**
	(Δ)	(0)	(0)	(+2)	(0)	4		
Male	Lightweight to Middleweight	0	2	1	0	3	4.12	0.249
	(Δ)	(0)	(+1)	(0)	(0)	3		
	Middleweight to Lightweight	1	3	2	1	7	1.73	0.631
	(Δ)	(-3)	(+1)	(+1)	(0)	7		
	Middleweight to Heavyweight	2	4	2	1	9	1.87	0.599
	(Δ)	(-2)	(+2)	(0)	(0)	9		
	Heavyweight to Middleweight	0	0	2	0	2	4.55	0.208
	(Δ)	(0)	(0)	(+1)	(0)	2		

Note: Δ represents the difference between the observed value and the expected theoretical value

Table 9. Group means (± standard deviations) for the items selected in the final psychosocial model.

Construct	H1	H2	Q1	Q2	Q3	Q4
Mastery approach	5.7 ± 1.0	6.0 ± 0.8	5.7 ± 1.0	5.6 ± 0.9	6.3 ± 0.8	5.8 ± 0.9
Concern over mistakes	2.4 ± 1.1	3.3 ± 1.6	2.3 ± 1.5	2.6 ± 0.9	3.7 ± 1.8	3.1 ± 1.5
Emotional stability	5.4 ± 1.4	4.6 ± 1.5	4.9 ± 1.5	5.9 ± 1.3	4.4 ± 2.0	4.8 ± 1.2
Openness to experience	4.8 ± 1.1	5.0 ± 0.9	4.9 ± 1.1	5.1 ± 0.6	4.9 ± 1.0	4.9 ± 1.0

Table 10. Summary statistics for all four classification algorithms in H1 vs H2 (and Q1 vs Q4) classification

Classifier	Accuracy	Sensitivity	Specificity	Area under ROC curve
Naïve Bayes	51.30%	0.591	0.421	0.493
(Q1 vs Q4)	(59.00%)	(0.640)	(0.5)	(0.6)
Support Vector Machine	46.30%	0.636	0.263	0.45
(Q1 vs Q4)	(63.60%)	(0.714)	(0.5)	(0.66)
J48 Decision Tree	63.40%	0.727	0.526	0.617
(Q1 vs Q4)	(86.30%)	(0.824)	(1)	(0.863)
K-Nearest Neighbor	73.20%	0.773	0.684	0.728
(Q1 vs Q4)	(81.90%)	(0.813)	(0.833)	(0.9)
All Classifiers	58.50%	0.682	0.473	0.572
(Q1 vs Q4)	(72.70%)	(0.748)	(0.708)	(0.756)

Accuracy = Correctly classified observations / total number of observations. Sensitivity = 1 – false positive rate. Specificity = 1 – false negative rate. Area under ROC curve is a measure of model's ability to correctly distinguish the two groups. ROC = Receiver operating characteristic.