Research Quarterly for Exercise and Sport

ISSN: 0270-1367 (Print) 2168-3824 (Online) Journal homepage: https://www.tandfonline.com/loi/urqe20

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To cite this article: Zackary S. Cicone, Clifton J. Holmes, Michael V. Fedewa, Hayley V. MacDonald & Michael R. Esco (2019): Age-Based Prediction of Maximal Heart Rate in Children and Adolescents: A Systematic Review and Meta-Analysis, Research Quarterly for Exercise and Sport, DOI: 10.1080/02701367.2019.1615605

To link to this article: https://doi.org/10.1080/02701367.2019.1615605

RESEARCH QUARTERLY FOR EXERCISE AND SPORT
https://doi.org/10.1080/02701367.2019.1615605

Age-Based Prediction of Maximal Heart Rate in Children and Adolescents: A Systematic Review and Meta-Analysis

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ABSTRACT

Purpose: Maximal heart rate (MHR) is an important physiologic tool for prescribing and monitoring exercise in both clinical and athletic settings. However, prediction equations developed in adults may have limited accuracy in youth. The purpose of this study was to systematically review and analyze the available evidence regarding the validity of commonly used age-based MHR prediction equations among children and adolescents. **Methods**: Included articles were peer-reviewed, published in English, and compared measured to predicted MHR in male and female participants <18 years old. The standardized mean difference effect size (*ES*) was used to quantify the accuracy of age-predicted MHR values and *a priori* moderators were examined to identify potential sources of variability. **Results**: The cumulative results of 20 effects obtained from seven articles revealed that prediction equations did not accurately estimate MHR (ES= 0.44, $p < .05$) by 6.3 bpm (bpm). Subgroup analyses indicated that the Fox equation (MHR = 220–age) overestimated MHR by 12.4 bpm (ES = 0.95, $p < .05$), whereas the Tanaka equation (MHR = 208–0.7*age) underestimated MHR by 2.7 bpm (ES = −0.34, $p < .05$). **Conclusions**: Age-based MHR equations derived from adult populations are not applicable to children. However, if the use of age-based equations cannot be avoided, we recommend using the Tanaka equation, keeping in mind the range of error reported in this study. Future research should control for potential pubertal influences on sympathetic modulation during exercise to facilitate the development of more age-appropriate methods for prescribing exercise intensity.

ARTICLE HISTORY
Received 7 January 2019
Accepted 29 April 2019

KEYWORDS
Aerobic; pediatric; exercise testing; youth

Maximal heart rate (MHR) is defined as the highest heart rate achieved during a maximal effort graded exercise test (GXT) and is characterized by a plateau in heart rate despite an increase in workload (Nes, Janszky, Wisløff, Støylen, & Karlsen, 2013). The strong, positive association between heart rate and oxygen uptake enables researchers to use heart rate as an indicator of physiological strain, with MHR representing the upper limit of cardiovascular function (Colantonio & Kiss, 2013; Mahon, Lee, & Hanna, 2010). MHR is commonly used to prescribe and monitor training intensity in sports and clinical rehabilitation settings because of its non-invasive nature (Mahon et al., 2010; Nes et al., 2013). However, since it is not always feasible or desirable to have participants perform maximal effort tests in order to determine MHR, it is often predicted using age-based regression equations. These equations are based on the well-established inverse association between age and MHR in adults (Gellish et al., 2007; Kostis et al., 1982; Robinson, 1938).

Age-based models for predicting MHR have been developed from a number of adult populations, including subjects with cardiovascular disease (Bruce, Fisher, Cooper, & Gey, 1974; Hammond, Kelly, & Froelicher, 1983), athletes (Londeree & Moeschberger, 1982), mentally impaired subjects (Fernhall et al., 2001), obese subjects (Miller, Wallace, & Eggert, 1993), and healthy men and women (Inbar et al., 1994; Tanaka, Monahan, & Seals, 2001). Perhaps the most common equation used within health and fitness is "MHR = 220 – age", an equation which was for a long time either not cited or incorrectly attributed to Karvonen or Astrand (Robergs & Landwehr, 2002). Robergs and Landwehr discussed the development of this equation in a 2002 paper, and have tied it to a 1971 publication by Fox, Naughton, and Haskell (Fox, Naughton, & Haskell, 1971). Of the published equations, the two most ubiquitous throughout the exercise science literature and health and fitness industry include i) the previously described equation of Fox et al. (referred to as the Fox equation), and ii) that described by Tanaka et al. (referred to as the Tanaka equation, MHR = 208–0.7*age) (Tanaka et al., 2001).

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Supplementary data for this article can be found on the publisher's website.

A major limitation of these equations is their lack of applicability to non-adult populations. The observed physiological phenomenon on which they are based – a decrease in MHR with increasing age – has been shown to be absent in children and adolescents (Lehmann, Keul, & Korsten-Reck, 1980; Rowland et al., 1996). Even when used in adult samples these equations result in prediction errors in excess of 10 bpm (Robergs & Landwehr, 2002), so their ability to estimate MHR in youth (note, the term "youth" in this paper refers to children and adolescents collectively) is likely even less accurate. Considering this, attempting to predict MHR in youth using age-based models may not be the most advisable practice.

Unfortunately, current exercise guidelines for children and adolescents are vague and do not provide objective metrics for prescribing aerobic exercise intensity (Donnelly et al., 2016). While this may suffice as general health guidelines, certain youth populations would benefit from more concrete recommendations. For example, coaches often monitor heart rate in youth athletes during practice to ensure they are maintaining an appropriate exercise intensity in relation to age-predicted MHR (Nikolaidis, 2014; Nikolaidis et al., 2014). Further, guidelines for clinical testing in children and adolescents with health concerns such as congenital heart disease use age-predicted MHR as a reference point for affirmation of satisfactory effort during some submaximal stress tests (Paridon et al., 2006). Age-based MHR is also used to determine exercise intensity in active recovery protocols for treating youth athletes with sport-related concussions (Gagnon, Grilli, Friedman, & Iverson, 2016; Halstead & Walter, 2010).

Considering the potential applicability to clinical and athletic populations, identification of age-appropriate and accurate methods for determining MHR would be of great benefit to pediatric health and sport professionals. Working towards this end, the purpose of this study was to systematically review and analyze the available evidence regarding the validity of age-based MHR prediction equations among children and adolescents, and to identify potential moderators that explain error in their estimates. Due to their development from adult populations, it was hypothesized that the equations found in the literature would inaccurately predict MHR in youth.

Methods

This study fully satisfies the criteria implied by the PRISMA Statement (*P*referred *R*eporting *I*tems for *S*ystematic *R*eview and *M*eta-*A*nalyses) (Moher, Liberati, Tetzlaff, Altman, & Group, 2009; Moher et al., 2015) and the AMSTAR Methodological Quality Tool (*A*ssessment of *M*ultiple *S*ys*T*em*A*tic *R*eviews) (Shea et al., 2007, 2009).

Procedures

Search strategy

The electronic database search included PubMed, Physical Education Index, SPORTDiscus, and Scopus. All databases were searched from inception through March 2018 using the following terms: (valid* OR evaluat*) AND (prediction AND equation) AND (max* AND (heart AND rate)) AND (young OR youth OR adolesce* OR child*). The following limiters were used to filter search results: peer-reviewed; English language; human studies. To supplement our electronic database searching, reference lists of included studies, relevant reviews, and previously published meta-analyses were manually searched for additional reports. Articles were included if they met the following *a priori* criteria: i) were peer-reviewed; ii) the full-text article was available in English; iii) included healthy human subjects; iv) included subjects that were less than 20 years of age, either exclusively or as a subgroup that was analyzed separate from participants aged 20 years or older; v) compared MHR measured during an incremental, exhaustive exercise test to MHR predicted from the Fox and/or Tanaka equations; vi) reported sufficient information to calculate the standardized mean difference effect size (*ES*) and its components (i.e., the means and standard deviations [*SD*s], standard errors, or 95% confidence intervals [*CI*s] of measured and predicted MHR; means and *SD*s, standard errors, or 95% *CI*s of the difference between measured and predicted MHR).

Methodological study quality and data extraction

Methodological study quality (MSQ) was assessed independently by two authors (ZSC and CJH) using a modified version of the TRIPOD prediction model validation guidelines (Collins, Reitsma, Altman, & Moons, 2015; Moons, Altman, Reitsma, Collins, & Transparent Reporting of a Multivariate Prediction Model for Individual Prognosis or Development, 2015). Study quality scores were interpreted as low (≤50%), moderate (50–79%), or high (≥80%). See online Supplemental Digital Content (SDC) 1 and SDC 2 for the amended guidelines and scoring criteria. Two authors (ZSC and MVF) independently reviewed potentially eligible titles, abstracts, and full-text articles identified during the literature search. After the final sample was identified, the same two authors extracted study information and coded the following variables: sample characteristics (age, sex, body mass index [BMI]), type of exercise test (laboratory or field-based test), and prediction equation used to estimate MHR, and MSQ. Disagreements were resolved by discussion or by consulting a third party (MRE). Requests for missing data were sent to two of the corresponding authors, both of whom provided the requested information (Colantonio & Kiss, 2013; Mahon et al., 2010).

Study outcomes and mean effect size calculation

The standardized mean difference *ES* was used to quantify the accuracy of age-based prediction equations, defined as the mean difference between predicted and measured MHR divided by the *SD* of the differences, correcting for small sample bias (Becker, 1988; Gibbons, Hedeker, & Davis, 1993). For studies with multiple comparisons (e.g., groups separated by sex or age group (Colantonio & Kiss, 2013; Nikolaidis, 2014), use of more than one prediction equation (Cicone, Sinelnikov, & Esco, 2018; Machado & Denadai, 2011; Mahon et al., 2010; Nikolaidis, 2014, 2015; Nikolaidis et al., 2014)), the effects were disaggregated and analyzed separately (Lipsey & Wilson, 2001). *ES*s with a positive value indicated that the prediction equation overestimated measured MHR. The magnitude of the absolute value of the *ES* was interpreted as small (≤0.20), medium (0.50), and large (≥0.80) (Cohen, 1988). Additionally, we provide the unstandardized mean difference (UMD, the mean difference between predicted and measured MHR in bpm) along with the pooled 95% limits of agreement as a supplement to *ES* in order to better contextualize our findings (Tipton & Shuster, 2017). Lack of consistency across *ES*s was estimated by the *Q* statistic (Cochran, 1954) and transformed into the I^2 statistic (and 95% *CI*s), which gauged the degree or extent of heterogeneity. The I^2 statistic was interpreted as low (25%), moderate (50%), and high (75%) (J. Higgins, Thompson, Deeks, & Altman, 2003; Huedo-Medina, Sánchez-Meca, Marín-Martínez, & Botella, 2006).

Moderator analyses and potential bias

We examined several *a priori* study-level moderators (MSQ, age, sex, BMI, prediction equation, and exercise test type) to determine which factor or combination of factors influenced the degree of accuracy between measured and predicted MHR (continuous and categorical moderator variables are defined in SDC 3). Each effect was weighted by the inverse variance and examined as a potential moderator in univariate analysis with maximum likelihood estimation of the random-effects weights (Lipsey & Wilson, 2001). Statistically significant univariate models were integrated into a multiple moderator model to determine which variables explained unique-between study variance. Due to the limited number of effects in our sample, we restricted the multiple moderator model to the two variables with the largest proportion of explained variance (J. P. Higgins & Green, 2011).

We visually examined a funnel plot for outliers and asymmetries in the *ES* distribution to identify potential publication or other reporting biases (J. Sterne, Egger, & Moher, 2011), as well as performing statistical tests of bias using Begg (Begg & Mazumdar, 1994) and Egger (Egger, Smith, Schneider, & Minder, 1997) methods. Additionally, we calculated the fail-safe N+ using random effects, which is the required number of unpublished or unretrieved null effects that would diminish the significance of the observed effect to a non-significant result (Rosenberg, 2005; Rosenthal, 1979). Although the fail-safe N+ statistic is not a robust method for detecting publication bias, we used it as an additional metric to inform our decision as to whether more sophisticated bias assessment methods were needed (Rosenberg, 2005).

Statistical analyses

Descriptive sample characteristics were summarized using the available data and are presented as mean ± *SD* unless otherwise stated. *ES* estimates are reported as mean and 95% *CI*s. Unstandardized mean differences and pooled 95% limits of agreement are reported as UMD ± 1.96**SD* bpm of the differences. Standardized beta (β) and its *p*-value, as well as coefficient of determination (R^2) are provided to quantify the relative contribution of each moderator to the variability in *ES*. Analyses used SPSS 23.0 (IBM Corp., Armonk, NY, USA) with macros for meta-analysis (Lipsey & Wilson, 2001), utilizing random-effects assumptions. Two-sided statistical significance for statistical tests was $p < .05$.

Results

Study selection and methodological quality

Our systematic search yielded 90 potentially relevant reports. After removing duplicates 77 were screened for inclusion, resulting in a final sample of seven studies published between 2011 and 2018. All studies yielded >1 comparisons, thus a total of 20 effects were available for quantitative analysis. Figure 1 shows the systematic search for potential reports and selection process of included studies. Overall, the seven articles included in our meta-analysis achieved moderate quality (74.5%), with scores ranging from 57.4% to 80.0%. Modified TRIPOD items least likely to be satisfied by the studies included: blinding of investigators to any portion of the study (0%); providing supplemental information (0%); justification of

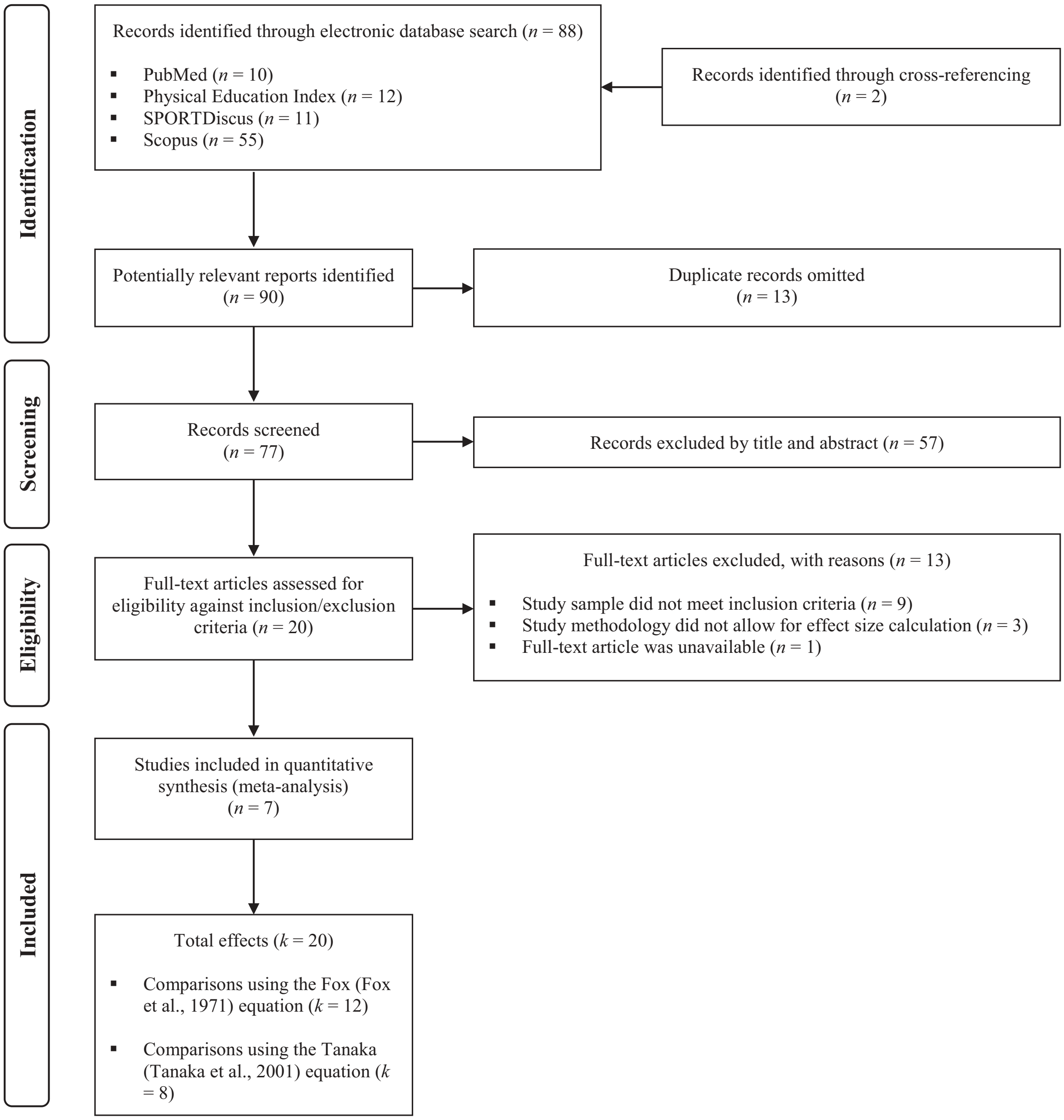

Figure 1. Flow chart detailing the systematic search, identification, screening, and selection of potential research studies (*n*), and extraction of effects (*k*).

sample size or post hoc power analysis (14.3%); discussion of handling missing data (14.3%); clear eligibility criteria of participants (14.3%); disclosure of funding (42.9%). Overall and itemized MSQ are provided in SDC 4.

Subject and study characteristics

Aggregate-level data from 648 (28.0% female) healthy children and adolescents (age, 13.0 ± 2.4 years) of normal weight (BMI, 20.9 ± 2.7 kg·m^{-2}) were included in our quantitative analysis. The average measured MHR value across the reviewed effects was 198.3 ± 8.9 bpm. See Table 1 for a summary of the studies included in our meta-analysis. All seven studies used the Fox equation to predict MHR (Cicone et al., 2018; Colantonio & Kiss, 2013; Machado & Denadai, 2011; Mahon et al., 2010; Nikolaidis, 2014, 2015; Nikolaidis et al., 2014). Six studies used both the Tanaka and Fox equations to predict MHR (Cicone et al., 2018; Machado & Denadai, 2011; Mahon et al., 2010; Nikolaidis, 2014, 2015; Nikolaidis et al., 2014). Predicted MHR values from the Fox and Tanaka equations were 206.4 ± 2.0 and 198.2 ± 1.1 bpm, respectively. Measured MHR was elicited using incremental exercise tests in all studies. However, the specific testing modality varied between studies. Four studies utilized a laboratory-based maximal-effort GXT on a motorized treadmill (Cicone et al., 2018; Colantonio & Kiss, 2013; Machado & Denadai, 2011; Mahon et al., 2010), while three studies used an exhaustive field-based test to

Table 1. Summary of subject characteristics, methods, and results from the seven included studies.

	Sample Characteristics				Study design		Primary Outcome Variables		Result
Author (citation)	Participants	*n* (% female)	Age (y)	BMI ($kg{\cdot}m^{-2}$)	Age-based prediction equation	Exercise Test Type	Predicted maximal heart rate (bpm)	Measured maximal heart rate (bpm)	Overestimate, underestimate or valid?
Colantonio & Kiss, 2013	Untrained females	40 (100)	12.5 ± 3.3	19.2[a]	Fox	GXT	207.5 ± 3.3	178.0 ± 18.8	Overestimate
	Trained females	34 (100)	11.9 ± 3.2	19.9[a]			208.1 ± 3.2	181.7 ± 13.2	Overestimate
	Untrained males	36 (0)	12.0 ± 3.1	18.9[a]			208.0 ± 3.1	180.3 ± 12.1	Overestimate
	Trained males	35 (0)	12.0 ± 3.2	19.8[a]			208.0 ± 3.2	184.0 ± 13.9	Overestimate
Machado & Denadai, 2011	Healthy children	69 (0)	12.6 ± 1.5	20.3[a]	Fox	GXT	207.4 ± 1.5	200.2 ± 8.0	Overestimate
					Tanaka		199.2 ± 1.1		Valid
Mahon et al., 2010	Athletic children	52 (40)	12.0 ± 3.1	20.5[a]	Fox	GXT	208.0 ± 3.0	201.0 ± 10.0	Overestimate
					Tanaka		200.0 ± 2.0		Valid
Nikolaidis, 2014	Athletic – under 12y	50 (0)	10.7 ± 0.8	18.3 ± 2.4	Fox	Field	209.3 ± 0.8	202.3 ± 8.2	Overestimate
					Tanaka		200.5 ± 0.6		Underestimate
	Athletic – under 15y	40 (0)	13.4 ± 0.8	20.9 ± 2.9	Fox	Field	206.6 ± 0.8	200.4 ± 8.5	Overestimate
					Tanaka		198.6 ± 0.6		Valid
	Athletic – under 18y	57 (0)	16.3 ± 0.8	22.5 ± 3.0	Fox	Field	203.7 ± 0.8	200.1 ± 6.8	Overestimate
					Tanaka		196.6 ± 0.6		Underestimate
Nikolaidis et al., 2014	Athletic females	47 (100)	13.4 ± 2.0	20.2 ± 2.8	Fox	Field	206.6 ± 2.0	200.9 ± 6.9	Overestimate
					Tanaka		198.6 ± 1.4		Valid
Nikolaidis, 2015	Athletic males	158 (0)	15.8 ± 1.5	21.4 ± 2.1	Fox	Field	204.2 ± 1.5	200.2 ± 7.9	Overestimate
					Tanaka		196.9 ± 1.0		Underestimate
Cicone et al., 2018	Athletic males	30 (0)	14.6 ± 0.6	20.3 ± 2.1	Fox	GXT	205.4 ± 0.6	205.0 ± 7.7	Valid
					Tanaka		197.8 ± 0.4		Underestimate

Note: BMI, body mass index; bpm, beats per minute; GXT, graded exercise test; $kg{\cdot}m^{-2}$, kilograms/meters squared; *n*, sample number; y, years. [a]BMI not provided, so value was calculated from reported mean height and weight. Equations: Fox (Fox et al., 1971), maximal heart rate = 220 – age; Tanaka (Tanaka et al., 2001), maximal heart rate = 208 – 0.7*age.

elicit MHR (Nikolaidis, 2014, 2015; Nikolaidis et al., 2014). Descriptions of the testing protocols are provided in SDC 5.

Accuracy of prediction equations

The cumulative results of 20 effects obtained from seven articles revealed that prediction equations, in general, overestimated measured MHR (*ES* = 0.44, 95% *CI*: 0.15 to 0.73, UMD = 6.3 ± 15.7 bpm) in youth (Figure 2). However, this mean *ES* lacked homogeneity, with Cochran's *Q* and the I^2 statistic indicating that the observed *ES*s were not consistent across the 20 effects (Q_{17} = 349.57, $p < .001$ and I^2 = 94.6%, 95% *CI*: 92.8% to 95.9%). It should be noted that although the I^2 is very high, meta-analyses with a limited number of studies (<20) may be underpowered to detect heterogeneity (Huedo-Medina et al., 2006). We used subgroup and meta-regression analyses to explore potential sources of variability.

Moderator analyses

Univariate meta-regression models revealed that age (β = −0.42, *p* = .0351), MSQ (β = −0.76, $p < .0001$) and prediction equation (β = −0.81, $p < .0001$) were significant sources of error in the accuracy of estimated and measured MHR. MSQ and prediction equation each explained a large proportion of between-study variability (R^2 values for MSQ and prediction equation were 57.8% and 65.3%, respectively), while age explained a much smaller proportion (R^2 =17.8%). Further subgroup analysis revealed that the Fox prediction equation overestimated MHR (*ES* = 0.95, 95% *CI*: 0.70 to 1.20, UMD = 12.4 ± 16.2 bpm) and the Tanaka prediction equation underestimated MHR (*ES* = −0.34, 95% *CI*: −0.63 to −0.05, UMD = −2.7 ± 5.8 bpm). Sex (β = 0.35, *p* = .0884), BMI (β = −0.38, *p* = .0590), and exercise test type (β = −0.35, *p* = .0915) did not significantly modulate the accuracy of predicted versus measured MHR in our sample. MSQ and prediction equation were included in a multiple moderator model due to their large β and R^2 values. Both variables remained significant when combined in the model, with MSQ (β = −0.4790, $p < .0001$) and prediction equation (β = −0.6846, $p < .0001$) collectively accounting for 88.5% of the variability observed in our sample.

Assessment of potential bias

Visual examination of our funnel plot revealed several potential outliers in the ES distribution of our sample (SDC 6). Publication bias was detected using both Egger (*z* = 3.76, *p* = .0002) and Begg (τ = 0.40, *p* = .0135) tests, though these tests are difficult to interpret in small meta-analyses with high heterogeneity (Sterne et al., 2011; Sterne, Gavaghan, & Egger, 2000). In addition, we determined the fail-safe N+ for the difference between predicted and measured MHR for both prediction equations. For the Fox equation, the random-effects fail-safe N+ estimated that 12.3 effects would be needed to overturn our significant result. For the Tanaka equation, the random-effects fail-safe N+ estimated that 9.4 effects would be needed to overturn our significant result.

Discussion

The primary aim of this paper was to systematically review and analyze the available evidence regarding the validity of age-based MHR prediction equations among male and female children and adolescents. To our knowledge, this systematic review and meta-analysis is the first to examine the predictive ability of these equations across studies. In addition to adhering to current methodological standards, this paper provides standardized mean differences between predicted and measured MHR values, unstandardized mean differences and pooled limits of agreement for practical application, and a quantitative analysis of potential moderators (MSQ, age, sex, BMI, prediction equation, exercise test type).

Measured MHR was similar across studies. The quantitative analysis demonstrated an overall moderate effect (*ES* = 0.44) between predicted and measured MHR in our sample. However, when separated by equation a large effect was shown for the Fox equation (*ES* = 0.95) while the Tanaka equation was shown to produce a moderate effect (*ES* = −0.34). The unstandardized mean differences and limits of agreement were also much smaller for the Tanaka equation than the Fox equation. These findings suggest that the Tanaka equation predicted MHR more accurately and accounted for more individual variability in our sample than the Fox equation. Moderator analyses showed that 88.5% of the variation in *ES* was accounted for by the prediction equation when accounting for MSQ.

Variation attributable to prediction equation was expected, as each was developed in very different populations. The Fox equation was derived from a review of 10 studies in older adults with cardiovascular disease

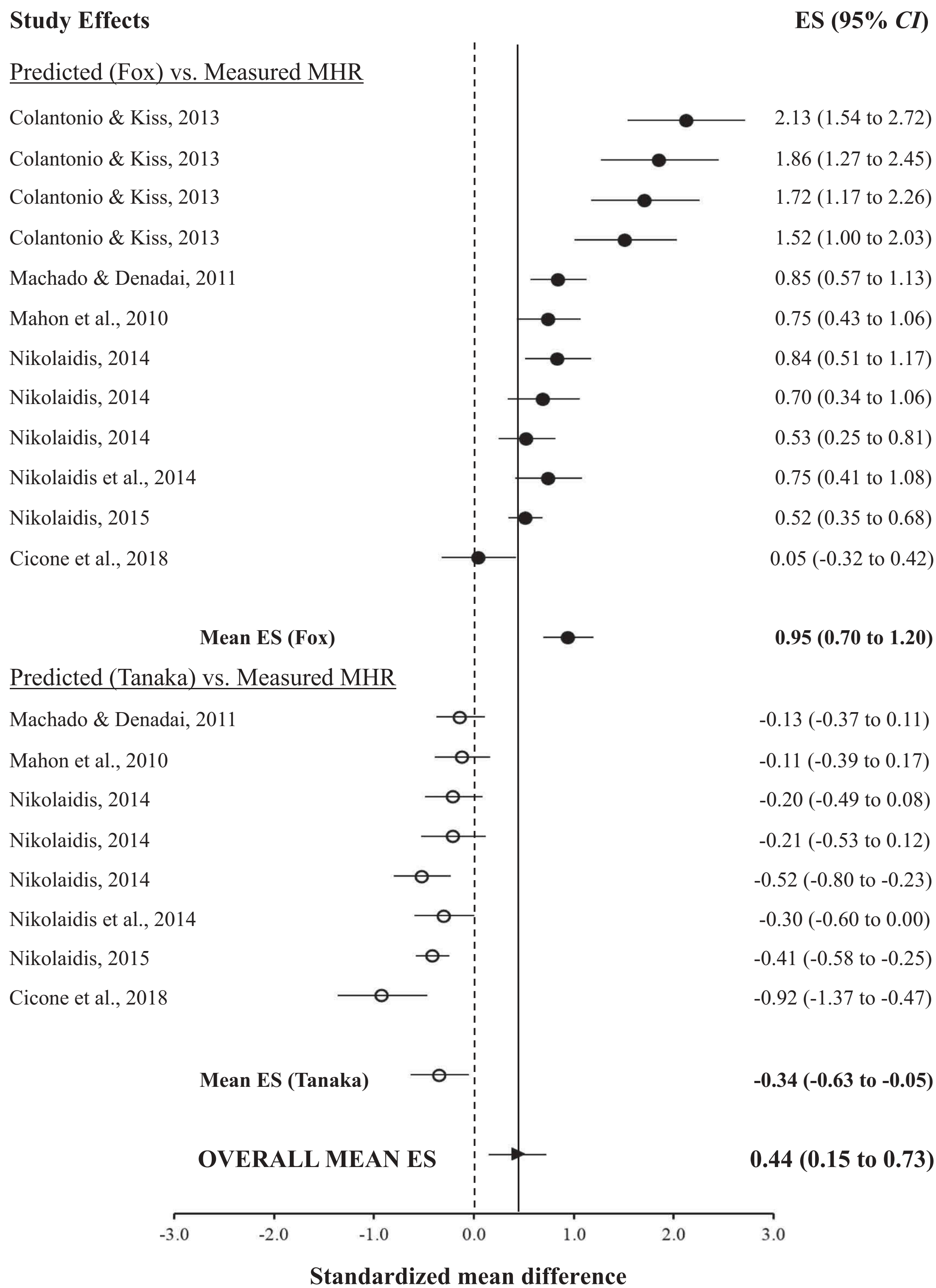

Figure 2. Forest plot of the 20 effects extracted from the seven studies, grouped by prediction equation. X-axis is the standardized mean difference. *ES*, effect size; *CI*, confidence interval; Fox, Fox et al. (Fox et al., 1971), prediction equation: Maximal heart rate (beats per minute) = 220 − age; Tanaka, Tanaka et al. (Tanaka et al., 2001) prediction equation: Maximal heart rate (beats per minute) = 208–0.7*age; Measured MHR, maximal heart rate obtained from a maximal-effort exercise test. Solid line represents overall mean effect size of 0.44, dashed line represents an effect size of 0.0.

(Fox et al., 1971; Robergs & Landwehr, 2002; Tanaka et al., 2001). Further, the Fox equation was determined without proper regression analysis, and subsequent attempts to replicate the findings were unsuccessful

(Robergs & Landwehr, 2002). The Tanaka equation was developed from a meta-analysis that examined the relationship between age and MHR in a sample of 18,712 healthy adults (Tanaka et al., 2001). The authors first used stepwise regression analysis to show that age explained approximately 80% of the observed variance in MHR, then cross-validated the resulting equation in a sample of 514 healthy men and women. Both studies excluded participants younger than 20 years of age (Fox et al., 1971; Tanaka et al., 2001), limiting their applicability to a younger population.

Aside from being developed from disparate samples, the Fox and Tanaka prediction equations are also based on an age-associated decline in MHR. Though this trend has been shown in adults (Gellish et al., 2007; Kostis et al., 1982; Robinson, 1938; Shargal et al., 2015), there is evidence that suggests that changes in MHR may occur independent of age in children (Åstrand, 1952; Gellish et al., 2007; Nes et al., 2013; Rowland et al., 1996; Shargal et al., 2015; Tanaka et al., 2001) and become stronger as age increases (Shargal et al., 2015). A proposed reason for this difference in the age-MHR relationship between children and adults is that prepubescent individuals may have blunted sympathetic modulation during exercise, possibly due to differences in sympathoadrenal regulation (Lehmann et al., 1980; Rowland et al., 1996). Another possible explanation for the low predictive ability of these age-based equations is a statistical limitation; the truncated age range associated with pediatric exercise (generally, a range of 10 years) could limit the ability of regression modeling to adequately account for changes in MHR, because the variability of MHR is much greater than the variability in age within the pediatric cohort. A large retrospective study by Shargal et al. found that MHR decreased at a rate of approximately 0.74 bpm per year for the overall study sample (>28,000 participants, ages 10–80 years), but was reduced to 0.52 bpm per year when examining younger participants within a smaller age range (10–20 years) (Shargal et al., 2015).

This attenuated decrease in MHR with increasing age in non-adult populations has led some authors to suggest the use of a fixed MHR value of 197 bpm (Gelbart, Ziv-Baran, Williams, Yarom, & Dubnov-Raz, 2017; Machado & Denadai, 2011), bypassing the measurement or estimation of MHR entirely. The previously mentioned study by Shargal et al. reported a mean MHR of 196.1 ± 7.6 bpm from a sample of 6,557 male and female subjects (age, 15.5 ± 2.4 years), though this analysis included subjects up to age 19.9 years (Shargal et al., 2015). A more recent large-scale retrospective study by Gelbart et al. examined a database of 627 maximal exercise tests from 433 adolescent athletes and reported a mean MHR of 197 ± 8.6 bpm (Gelbart et al., 2017). Additionally, the authors sought to identify an accurate method of predicting MHR in youth, as well as examine factors influencing MHR. Their sample was similar to our aggregate sample in terms of age (13.7 ± 2.1 years), BMI (19.9 ± 3.4 kg·m^{-2}), and percent females (29.6%). Using multiple regression analysis, they identified resting heart rate (RHR), fitness level, body mass, and percent fat as statistically significant predictors of MHR, though they collectively accounted for less than 30% of the observed variance in MHR. The authors ultimately recommended the use of a fixed MHR value of 197 bpm for children and adolescents due to the low predictive ability of the regression models (Gelbart et al., 2017).

Three of the reviewed studies also attempted to update MHR prediction models, with two developing novel equations (Mahon et al., 2010; Nikolaidis, 2015) and one examining the effects of age, sex, and training status on MHR (Colantonio & Kiss, 2013). Mahon, Lee, and Hanna reported two equations using RHR and maturity offset (MO) from a sample of 52 boys and girls between ages 7 and 17 years (Equation 1: MHR = 166.7 + 0.46*RHR + 1.16*MO, $R^2 = 0.29$, $SEE = 8.3$, $p < .05$; Equation 2: MHR = 158.4 + 0.44*RHR + 0.68*age, $R^2 = 0.29$, $SEE = 8.54$, $p < .05$), though the authors state these did not improve the explained variance in MHR (Mahon et al., 2010). Nikolaidis described a sport-specific equation from a sample of 162 youth male soccer players with a similar standard error and low predictive ability (MHR = 223–1.44*age, $r = -0.27$, $SEE = 7.6$) (Nikolaidis, 2015).

A potential moderator that warrants further investigation is the pubertal status of the participants. The studies reviewed in this meta-analysis included participants ranging in age from 7 to 18 years. Considering normal pubertal development occurs between the ages of 9–13 in girls and 10–14 in boys (Bitar, Vernet, Coudert, & Vermorel, 2000), it is reasonable to assume that the study participants were not homogeneously prepubescent or pubescent. Research designs using mixed-sex samples (Colantonio & Kiss, 2013; Mahon et al., 2010) may compound this problem, as girls tend to begin puberty earlier than boys (Bitar et al., 2000; Solorzano & McCartney, 2010). We identified one study in the literature that categorized subjects as pre- and post-puberty; however, the authors reported no significant moderating effect (Gelbart et al., 2017). Unfortunately, the retrospective nature of the study precluded any physical assessment of the participants, so pubertal status was determined solely by age-based threshold values (14 years for girls, 16 years for boys).

We recommend that future investigators stratify participants by pubertal status using valid methodology, e.g., a clinical exam by a trained clinician to control for any latent influences of puberty. When physical examination is impractical, self-assessment tools such as the pubertal development scale (Petersen, Crockett, Richards, & Boxer, 1988) may be used, though their validity and reliability is questionable in comparison (Coleman & Coleman, 2002; Dorn & Biro, 2011; Taylor et al., 2001). It should also be noted that pubertal development may be expressed as a continuous or categorical variable depending on the needs of the researcher (Petersen et al., 1988), and that self-assessment tools may be useful for dichotomizing participants as "pre-pubescent" and "pubescent" (Rasmussen et al., 2015). As an expanded discussion of pubertal status determination is beyond the scope of this paper, we recommend a comprehensive review on the topic by Dorn and Biro (2011), which addresses the issues involved in the measurement of puberty. Further, practical guidelines are laid out to help researchers determine the most appropriate methods for assessing pubertal status in Dorn, Dahl, Woodward, and Biro (2006).

Methodological disparities also impose significant challenges when trying to describe adolescent responses to maximal effort exercise. Specifically, there is a lack of consensus regarding what constitutes adequate secondary criteria for determining a maximal effort (Armstrong & Welsman, 1994; Washington et al., 1994). Various standards have been adopted for assessment in youth, including rating of perceived exertion ≥8, respiratory exchange ratio ≥1.00, attainment of an MHR ≥ 180 bpm, and outward physical signs of intense effort (hyperpnoea, facial flushing, ataxic gait, and inability to keep up with the treadmill) (Armstrong & Welsman, 1994; Cicone et al., 2018; Colantonio & Kiss, 2013; Gelbart et al., 2017; Machado & Denadai, 2011; Mahon et al., 2010). Unfortunately, these criteria are not applied consistently, determining if a true maximal effort was attained is difficult. The incongruent use of these testing criteria may help to explain the high heterogeneity observed in *ES*s, since not all studies defined criteria for determining achievement of a maximal effort.

Testing environment is another potential source of variability in the observed *ES*s. Specifically, testing location and mode of exercise may impact subject performance on maximal effort tests. For example, Williford, Scharff-Olson, Duey, Pugh, and Barksdale (1999) reported that youth male soccer players (mean age, 12.62 years) achieved higher MHR values during the 20-m shuttle run test compared to a treadmill GXT, though their sample was limited to 13 athletes. Further, both youth and adult subjects have been reported to achieve higher MHR during treadmill-based tests compared to cycling tests (Turley & Wilmore, 1997). Additionally, for younger children (pre-puberty), localized fatigue on the cycle may be exacerbated due to a predominance of type I muscle fibers and reduced glycolytic capacity (Boisseau & Delamarche, 2000). Although we did not find that testing conditions significantly modulated the accuracy of the prediction equations (see SDC 3), our sample of included studies was small (seven studies, yielding 20 effects), homogenous in terms of exercise mode (i.e., running) and split in terms of testing environment (50% laboratory tests, 50% field tests). As such, it is difficult to comment on the impact of testing environment on MHR. Future studies should be designed to determine the influence (if any) testing conditions have on MHR in children and adolescents.

This systematic review and meta-analysis is not without limitations. A systematic review and meta-analysis can only evaluate the cumulative body of research retrieved through the search process. Although the original authors were contacted for missing or incomplete data, and a manual search was performed in addition to the electronic database search, only databases accessible through the university library system were at the disposal of the authors. The specific keywords used were intentionally broad and inclusive to increase the sensitivity of the electronic database search, though additional or alternative keywords could have potentially yielded different results. Searches were also limited to English text only and may not include additional relevant publications in other languages. Despite these limitations, the authors feel confident that all relevant peer-reviewed articles meeting the outlined criteria were identified and included in the current review.

The search strategy excluded grey literature, which can lead to over-reporting of statistically significant findings and an inflated effect size, thereby increasing the risk of introducing bias into the review (Conn, Valentine, Cooper, & Rantz, 2003; Hopewell, McDonald, Clarke, & Egger, 2007). Additionally, the use of aggregate-level data rather than individual patient data has been shown to potentially produce misleading results, particularly if the studies are biased (Stewart & Parmar, 1993). However, the probability of potential bias is likely small given that the validation studies of these equations in children sought to find no significant difference between predicted and measured MHR, whereas inflated effect sizes would be more of a concern if the primary aim was to find significant differences. For this paper, the required aggregate data were available from the publications, so there was minimal benefit to utilizing the individual approach (Riley, Lambert, & Abo-Zaid, 2010).

Conclusions

In summary, the Fox equation overestimated MHR by 12.4 bpm and the Tanaka equation underestimated MHR by 2.7 bpm in our aggregate sample of children and adolescents. Additionally, tighter pooled limits of agreement were observed from the Tanaka equation (± 5.8 bpm) than the Fox equation (± 16.2 bpm), indicating that the Tanaka equation produces less mean bias and accounts for more individual variation in MHR. The findings of this study lead us to recommend that the Fox equation not be used to estimate MHR in a youth population. The Tanaka equation represents an acceptable alternative to the Fox equation, as it resulted in less bias between measured and predicted MHR and a reduced range of error. However, we feel strongly inclined to caution practitioners to interpret MHR predicted from this equation carefully due to the considerable variability observed in this analysis. Future research in this area should stratify participants by pubertal status using valid clinical or self-assessment methods to minimize confounding effects of puberty on sympathetic responses to exercise. Well-defined secondary criteria should also be utilized to allow for better cross-study analysis and to ensure that a true maximal effort is being attained. These suggestions may help standardize the assessment of youth populations so that ultimately more appropriate recommendations can be made when it comes to prescribing and monitoring exercise training intensities for children and adolescents.

What does this article add?

This systematic review and meta-analysis is, to our knowledge, the first paper to quantify the accuracy of maximal heart rate prediction equations in children and adolescents. Despite the dearth of research on this topic, the equations explored here are commonly employed throughout the exercise science and health fields to assess and prescribe aerobic exercise in youth. This paper shows that equations derived from adult populations are not applicable to children, which is likely a reflection of discrepancies in sympathetic response to aerobic exercise, and thus should be avoided. However, if the use of age-based MHR prediction equations cannot be avoided, we recommend using the Tanaka equation while keeping in mind the prediction error reported in our analysis.

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