Review Article

Meta-analysis of age-based maximum heart rate prediction equations: validating existing models across diverse populations

Parveen Kumar

Department of Physical Education, Chaudhary Ranbir Singh University, Jind, Haryana, India

Correspondence: parveenkumar@crsu.ac.in

Abstract

Purpose: Maximal heart rate (MHR) plays a crucial role in guiding exercise recommendations and monitoring in both clinical and sports contexts. Nevertheless, prediction equations designed for adults may not accurately predict MHR in youth. This study aims to systematically review and analyze the existing evidence on the validity of commonly used age-based MHR prediction models across participants of different ages. ***Methods*****:** The inclusion criteria encompassed peer-reviewed articles published in English that compared measured and predicted MHR values in male and female participants. To gauge the accuracy of age-predicted MHR values, the standardized mean difference effect size (ES) was employed. Furthermore, predefined moderators were examined to identify potential sources of variability. ***Results***: The cumulative findings from 29 effects obtained from nine articles demonstrated that prediction equations did not statistically significantly differ from zero MHR (ES= 0.24, p = 0.48), while individual effects (z = 1.99, p < .0.05) varied across the studies. Subgroup analyses indicated that the Fox, Nes and Londeree equations tended to overestimate MHR, while the Tanaka, Gelish and Arena equations have better accuracy with less mean bias. ***Conclusion***: Age-based MHR equations vary across the different age groups. However, if the use of age-based equations is unavoidable, our recommendation is to employ the Tanaka equation, taking into account the reported range of error in this study.

Keywords: Exercise testing, Training Load, Heart Rate

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Introduction

Maximum heart rate (MHR) is a crucial physiological parameter with various applications in sports and clinical settings (Berglund et al., 2019). It represents the highest number of heartbeats per minute an individual can achieve during intense exercise or stress (Nes et al., 2013). MHR can provide valuable information for training, performance assessment, and medical evaluation (Chauhan & Kumar, 2023; Dhillon & Malik, 2023a, 2023b; F. A. Kumar, 2023; Yadav et al., 2023). It is often used to set exercise intensity in endurance training both during traditional endurance exercise and even more so during high-intensity interval training. Commonly, the intensity during high-intensity training (HIT) is set at 85–95% of HRmax, and the percentage of HRmax reached during HIT is important for improving cardiorespiratory fitness (Moholdt et al., 2014). The robust and affirmative correlation between heart rate and oxygen consumption allows researchers to utilize heart rate as a marker of physiological stress, with Maximum Heart Rate (MHR) signifying the upper threshold of cardiovascular capacity (Colantonio & Peduti Dal Molin Kiss, 2013; Mahon et al., 2010). Heart rates vary between individuals of different physical fitness statuses. Generally, untrained individuals have high HR values both in rest and maximal physical exertion states, when compared to trained individuals (Achten & Jeukendrup, 2003;

Cook et al., 2006). Data also indicate that physical training causes reduced HRmax as a result of cardiac pump and autonomic nervous system adaptations that are made in order to achieve an efficient cardiac output. In addition, elevated HR at rest is considered to be an independent predictor of mortality in the general population and in subjects with cardiovascular disease (Caetano & Alves, 2015; Cook et al., 2006).

However, since it is not always feasible or desirable to have participants perform maximal effort tests in order to determine maximum heart rate (MHR), it is often predicted using age-based regression equations. For HR to be a valid measure of exercise intensity, we need to know the MHR of the individual. In clinical practice, HR is often reported as a percentage of age-predicted MHR. The traditional formula for age-predicted MHR is 220 – age (Fox & Haskell, 1968; Lester et al., 1968). These equations are based on a well-established inverse relationship between age and MHR in different populations. These models have been developed from diverse populations having various kinds of physical and health-related alterations i.e., cardiovascular disease (Bruce et al., 1974), Trained runners and cyclist (Kasiak et al., 2023), Soccer Players (C. D. Silva et al., 2013), Volleyball players (Papadopoulou et al., 2019), children, adolescents and old age individuals of both genders (Arena et al., 2016; Machado & Denadai, 2011; V. A. P. da Silva et al., 2007), Obese (Heinzmann-Filho et al., 2018), and sedentary persons(Sarzynski et al., 2013).

Accurate determination of MHR is of paramount importance in both clinical and athletic settings. It serves as a fundamental parameter for designing exercise programs, assessing cardiovascular health, and making informed decisions regarding intensity levels during physical activities. Consequently, ensuring the reliability of MHR prediction equations is essential for optimizing the well-being and performance of individuals across a broad spectrum of ages. Therefore, this research aims to bridge the gap between existing MHR prediction equations and the diverse populations they are applied. By conducting a meta-analysis that includes individuals of all ages, we seek to validate and refine these models, ultimately enhancing their clinical and practical utility in promoting cardiovascular health, optimizing athletic performance, and ensuring safe and effective exercise prescription across the lifespan. It was hypothesized that the equations extracted from existing literature would demonstrate inaccuracies when predicting maximum heart rates in the different aged populations.

Methods

This study adopted the criteria implied by the revised PRISMA statement (*Preferred Reporting Items for Systematic Review and Meta-Analysis*) (Page et al., 2021).

Procedure

Search Strategy

The electronic database search encompassed PubMed, and Scopus. We conducted searches across selected databases, spanning from their inception through April 2023. The search query employed the following terms: (valid* OR evaluat*) AND (prediction AND equation) AND (max* AND (heart AND rate)) AND (young OR youth OR adolescent* OR child* OR adult* OR older adult*). The ‘English language’, ‘human studies’, and ‘peer-reviewed’ were the limiters used to filter search results. In addition to electronic database searches, we conducted manual searches of reference lists in the included studies, relevant reviews, and previously published meta-analyses to identify any additional reports. We included articles that met the following predetermined criteria: (i) they were peer-reviewed; (ii) the full-text article was available in English; (iii) they involved healthy human subjects; (iv) no special restrictions have been made regarding the age of the participants. The studies including participants having different ages i.e., children to older adults have been included; (v) they compared maximal heart rate (MHR) measured during an exhaustive incremental exercise test to MHR predicted using the Fox, Tanaka or other equations; vi) they provided sufficient information to calculate the standardized mean difference effect size (ES) and its components, including the means and standard deviations (SDs), standard errors, or 95% confidence intervals (CIs) of both measured and predicted MHR, as well as the means and SDs, standard errors, or 95% CIs of the difference between measured and predicted MHR.

Methodological study quality and data extraction

A modified version of the TRIPOD prediction model validation guidelines (Heus et al., 2019; Moons et al., 2015) was used to assess the study quality. Study quality scores were interpreted as low (≤50%), moderate (50 – 79 %), or high (≥80%). See Guidelines **(Supplemental Content, SC 1)** and scoring criteria in online supplemental content **(SC 2)**. Two authors (LS and JPS) 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 (number of subjects (N), age, sex, body mass index [BMI], Vo2max), type of exercise test (laboratory or field-based test), and prediction equation used to estimate MHR, mean and SD of predicted and measured MHR. Ten MHR prediction equations (**See Table 1)** have been analyzed, and disagreements were resolved by discussion or by consulting a third party (RPA).

Study outcomes and mean effect size calculation

Effects Size (ES) was calculated using standardized mean difference which 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 (Andrade, 2020; Becker, 1988; Rice & Harris, 2005). The studies containing multiple comparisons and using more than one prediction equation (Heinzmann-Filho et al., 2018; Kasiak et al., 2023; C. D. Silva et al., 2013; V. A. P. da Silva et al., 2007), the effects were disaggregated and analyzed separately. *ESs* with positive values indicated that the prediction equation overestimated measured MHR, while those with negative values showed underestimated 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 percentage prediction error as a supplement to ES in order to better contextualize our findings (Guang et al., 1995). Consistency across ESs was estimated by *Q* statistics (Cochran, 1954) and transformed into the I^2 statistic (and 95% CIs), which gauged the degree or extent of heterogeneity. The I^2 statistic was interpreted as low (25%), moderate (50%), and high (75%) (Higgins et al., 2003; Huedo-Medina et al., 2006a).

Moderator analysis and publication bias

We examined several a priori study-level moderators (MSQ, age, BMI, Vo2 max, participants, 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 moderators are defined in **SC 5**). 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 variances.

We visually examined a funnel plot for outliers and asymmetries in the ES distribution to identify potential publication or other reporting biases (Sterne et al., 2008) as well as performing statistical tests of bias using Begg (Begg & Mazumdar, 1994) and Egger(Egger et al., 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).

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Table 1 Study Design and Subject Characteristics

studies	Participants	Exercise Test Type	Prediction Equation	Age	BMI	Vo2 max	N (%Female)	MHR				PE
								Predicted		*Observed*		
								Mean	*SD*	*Mean*	*SD*	
(C. D. Silva et al., 2013)	Soccer Players	Soccer Match (F)	Fox et al	14 (0.6)	-	49.5 (2)	18 (0)	205	0.6	202	8	1.485
		Soccer Match (F)	Tanaka et al	14 (0.6)	-	49.5 (2)	18 (0)	198	0.4	202	8	-1.980
		Soccer Match (F)	Nes et al.	14 (0.6)	-	49.5 (2)	18 (0)	202	0.4	202	8	0.000
(Heinzmann-Filho et al., 2018)	Obese	(CPET) (L)	Fox et al	16.8 (1.2)	35.69 (4.7)	26.9 (4.5)	59 (25)	203.2	1.2	190	9.2	6.947
		(CPET) (L)	Tanaka et al	16.8 (1.2)	35.6 (4.7)	26.9 (4.5)	59 (25)	196.3	0.8	190	9.2	3.316
		(CPET) (L)	Gelish et al	16.8 (1.2)	35.6 (4.7)	26.9 (4.5)	59 (25)	195.3	0.8	190	9.2	2.789
		(CPET) (L)	Heinzmann et al	16.8 (1.2)	35.6 (4.7)	26.9 (4.5)	59 (25)	191.9	0.6	190	9.2	1.000
(Arena et al., 2016)	Healthy	MET (L)	Arena et al	43 (12)	26 (5.4)	36.1(10.6)	4796 (35)	178.3	16	178	14	0.169
(V. A. P. da Silva et al., 2007)	Elderly Healthy	GXT (L)	Fox et al	67.1 (5.16)	27.68 (3.48)	22.24 (4.93)	93 (100)	152.9	5.1	145.5	12.5	5.086
		GXT (L)	Tanaka et al	67.1 (5.16)	27.68 (3.48)	22.24 (4.93)	93 (100)	161.0	3.9	145.5	12.5	10.653
(Machado & Denadai, 2011)	Healthy Boys	PMET (L)	Fox et al	12.6 (1.5)	47.3 (14.1)	-	69 (0)	207.4	1.5	200.2	8.0	3.596
		PMET (L)	Tanaka et al	12.6 (1.5)	47.3 (14.1)	-	69 (0)	199.2	1.1	200.2	8.0	-0.500
(Kasiak et al., 2023)	Trained Runners	CPET (L)	Nes et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	188.23	5.20	184.60	9.79	1.966
		CPET (L)	Machado et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	189.54	6.50	184.60	9.79	2.676
		CPET (L)	Tanaka et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	183.09	5.68	184.60	9.79	-0.818
		CPET (L)	Fox et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	184.42	8.12	184.60	9.79	-0.098
		CPET (L)	Londeree et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	181.00	5.77	184.60	9.79	-1.950
		CPET (L)	Inbar et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	181.43	5.56	184.60	9.79	-1.717
		CPET (L)	Gellish et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	182.09	5.68	184.60	9.79	-1.360
		CPET (L)	Arena et al	33.58(8.12)	24.04 (2.65)	53.24 (7.12)	4043(16.47)	183.68	5.85	184.60	9.79	-0.498
(Kasiak et al., 2023)	Trained Cyclist	CPET (L)	Tanaka et al	36.88(9.03)	24.04 (2.65)	51.67 (7.86)	4043(16.47)	182.19	6.32	182.66	10.28	-0.257
		CPET (L)	Fox et al	36.88(9.03)	24.04 (2.65)	51.67 (7.86)	4043(16.47)	183.12	9.03	182.66	10.28	0.252
		CPET (L)	Londeree et al	36.88(9.03)	24.04 (2.65)	51.67 (7.86)	4043(16.47)	180.08	6.42	182.66	10.28	-1.412
		CPET (L)	Fairbarn et al	36.88(9.03)	24.04 (2.65)	51.67 (7.86)	4043(16.47)	177.77	5.69	182.66	10.28	-2.677
		CPET (L)	Arena et al	36.88(9.03)	24.04 (2.65)	51.67 (7.86)	4043(16.47)	182.75	6.50	182.66	10.28	0.049
(Papadopoulou et al., 2019)	Volleyball Players	20 m SRT (F)	Fox et al	13.3 (0.7)	21.1 ± 2.2	-	71 (100)	206.7	0.7	199.9	8.6	3.402
		20 m SRT (F)	Tanaka et al	13.3 (0.7)	21.1 ± 2.2	-	71 (100)	197.3	0.6	199.9	8.6	-1.301
(Sarzynski et al., 2013)	Sedentary Persons	MET (L)	Fox et al	33.8 (13.2)	26.5±5.5	31±8.7	762 (56)	186.2	13.2	184.4	14.2	0.976
		MET (L)	Tanaka et al	33.8 (13.2)	26.5±5.5	31±8.7	762 (56)	184.3	9.2	184.4	14.2	-0.054

CPET = Cardio pulmonary exercise test, MET = Maximal Exercise Test, GXT = Graded Exercise Test, PMET = progressive maximal exertion test, SRT = shuttle run test, PE = Percentage error. (F) = Field Test Type, (L) Laboratory Test Type. Fox et al: 220 – age, Tanaka et al: 208 – (0.7× age), Nes et al: 211 – (0.64 × age), Heinzmann et al: 200 – (0.48 × age), Machado et al: 218 – (0.8 × age), Londeree et al: 206.3 – (0.711 × age), Inbar et al: 205.8 – (0.685 × age), Gellish et al: 207 – (0.7 × age), Arena et al: 209.3 – (0.72 × age), Fairbarn et al: 209.3 – (0.72 × age).

Results

Study selection and methodological Quality

Our systematic exploration of the literature identified a pool of 151 potentially relevant reports. Following the elimination of duplicates, we meticulously screened 129 of these reports for their suitability for inclusion. This rigorous process ultimately led to the inclusion of nine studies, all of which were published between 2007 and 2023. These nine studies provided a wealth of data, encompassing more than one comparison each, resulting in a total of 29 distinct effects available for our quantitative analysis. For a visual representation of our search and selection process, please refer to **Figure 1**. In terms of the quality of the studies included in our meta-analysis, we found that they collectively achieved a moderate level of quality, with an average score of 76.97%. Individual scores within this range varied between 62.96% and 88.0%. (**See SC 3**)

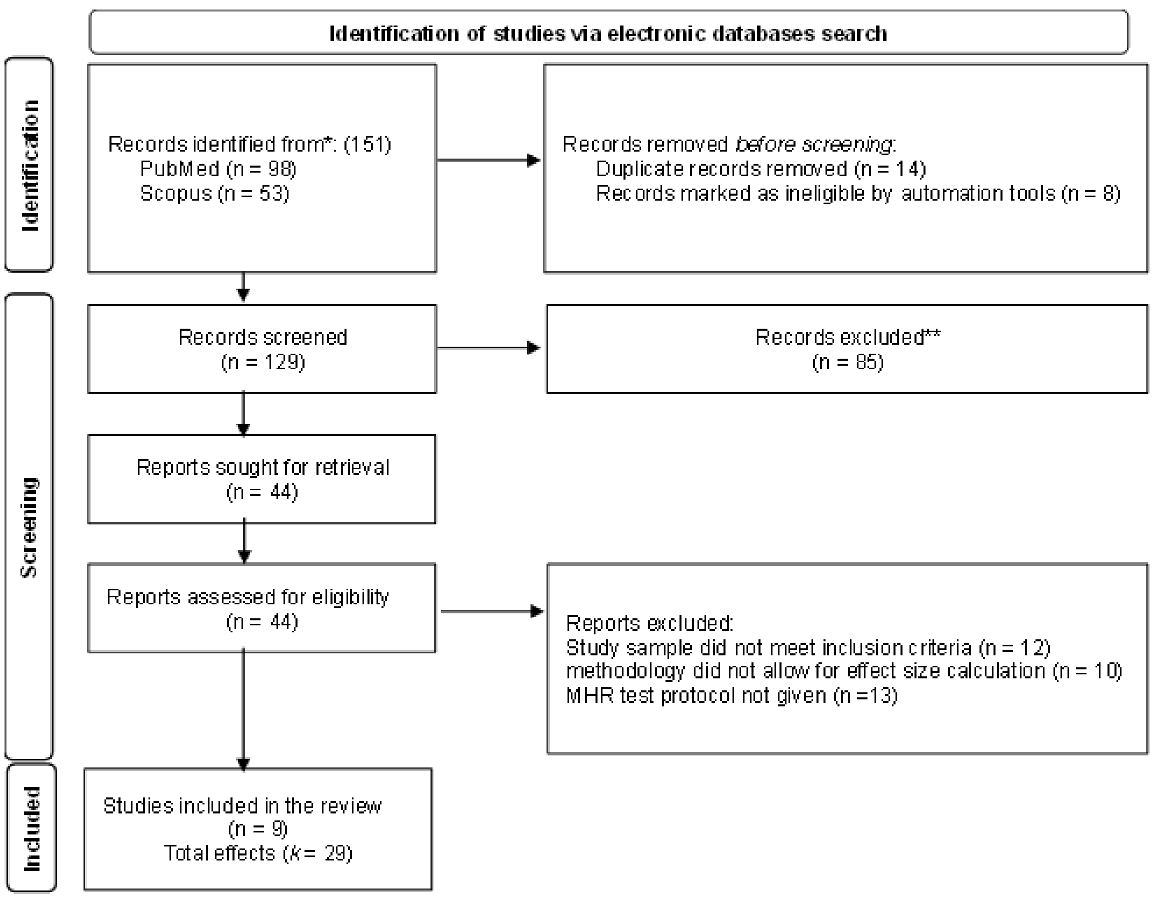

Figure 1. Flow chart detailing the systematic search, identification, screening and selection of potential research studies (n), and extraction of effects (*k*)

Subjects and Study Characteristics

A total of 11180 (27.45% female) healthy subjects aged from 14 to 67 years (age 29.61±14.53 years) and having slightly higher fat (BMI 26.31±4.53) were included in the study. The body mass index was showing slightly higher (≥25) due to the studies included obese (Heinzmann-Filho et al., 2018), older adults (V. A. P. da Silva et al., 2007), and sedentary (Sarzynski et al., 2013) participants. The rest of the studies included athletes of different disciplines. The capacity of maximal oxygen consumption [43.31±12.20 mL/(kg·min)] of the participants was reported in the index of above average. The average predicted MHR value across the reviewed effects were varies among the equation's types, i.e., Fox: 192.26±19.86 bpm, Tanaka: 187.67±12.98 bpm, Nes: 195.11±9.7 bpm, Gelish: 186.83±7.34 bpm, Londeree: 180.54±0.65 bpm, Arena: 183.21±6.53 bpm **See Table 1** for a summary of the studies included in our meta-analysis. Out of the total (nine) studies, 8 studies used Fox and Tanaka equations to Predict MHR. Some studies used to validate multiple equations. Two studies (Kasiak et al., 2023; C. D. Silva et al., 2013)used the Nes Equation, while, Gelish (Heinzmann-Filho et al., 2018; Kasiak et al., 2023), Londeree (Kasiak et al., 2023), Arena (Kasiak et al., 2023), and four other equations were used simultaneously in the included studies. The summary of the MHR prediction equations used in our meta-analysis is presented in **Table 1**. Measured MHR was elicited using various methods of incremental exercise tests in the context of laboratory and field settings in all studies. However, the specific testing modality varied between studies. Two studies used field settings to elicit measured MHR of the participants. Soccer match (C. D. Silva et al., 2013) and 20 m shuttle run (Papadopoulou et al., 2019) methods were used in field settings. Seven studies used the laboratory-based setting to elicit MHR. Cardiopulmonary exercise test (CPET) (Heinzmann-Filho et al., 2018; Kasiak et al., 2023), GXT (V. A. P. da Silva et al., 2007), progressive maximal exertion test (PMET) (Machado & Denadai, 2011), maximal exercise test (MET) (Arena et al., 2016; Sarzynski et al., 2013) methods were used as incremental exercise test to achieve MHR on a motorized treadmill. Subjects' fitness status was also varying among the selected studies. The subjects were divided into athletes and non-athlete participants. In athletes, Soccer players (C. D. Silva et al., 2013), Runners & Cyclist (Kasiak et al., 2023), and Volleyball players (Papadopoulou et al., 2019) were included.

Outcomes of Prediction Equations

The cumulative outcomes of 29 effects obtained from nine articles revealed that prediction equations, in general, overestimated measured MHR (ES = 0.21, 95% CI: 0.08 to 0.34, p = 0.07, UMD = 1.67, 95% CI: -0.11 ± 3.44 bpm). However, this mean ES lacked homogeneity, with Cochran's Q and the I^2 statistic indicating that the observed ESs were not consistent across the 29 effects (Q = 3147.77, p < .000 and I^2 = 99.9%). 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., 2006b). We used subgroup and meta-regression analyses to explore potential sources of variability.

Table 2 Summary of Sub-group analysis in the context of standardized mean difference (SMD)

Equation	Effect Size	Std. Error	Z	Sig. (2-tailed)	95% Confidence Interval		Heterogeneity Statistics		
					Lower	Upper	*Tau²*	*H²*	*I² (%)*
Fox	.610	.1057	5.768	<.001	.403	.817	.469	68.377	98.5
Tanaka	.139	.1000	1.391	.164	-.057	.335	.565	221.758	99.5
Nes	.463	.0225	20.572	<.001	.419	.507	.000	1.00	0.00
Gelish	.233	.5624	.414	.679	-.869	1.335	.298	306.275	99.7
Londeree	-.375	.0735	-5.096	<.001	-.519	-.230	.010	21.442	95.3
Arena	-.052	.0623	-.832	.405	-.174	.070	.007	15.66	93.3
Others	-.023	.2304	-.102	.919	-.475	.428	.235	366.318	99.7
Overall	.247	.0673	3.075	.002	.075	.339	.413	405.378	99.8

Sub-Group Analysis

Sub-group analysis depicted that Fox prediction equation overestimated MHR (ES = 0.61, 95% CI: 0.403 to 0.817, p < 0.001, UMD = 5.55, 95% CI: 2.197 ± 8.910 bpm). The ES measured through Tanaka equation was not statistically significantly different from zero (ES = 0.13, 95% CI: -0.057 to 0.335, p = 0.164, UMD = 1.49, 95% CI: -2.874 ± 5.864 bpm). Nes equation overestimated MHR (ES = 0.46, 95% CI: 0.419 to 0.507, p < 0.001, UMD = 2.302, 95% CI: -1.125 ± 5.729 bpm). The ES measured through Gelish equation was not statistically significantly different from zero (ES = 0.23, 95% CI: -0.869 to 0.133, p = 0.679, UMD = .954, 95% CI: -3.406 ± 5.314 bpm). Londeree prediction equation underestimated MHR (ES = -0.37, 95% CI: -0.519 to -0.230, p < 0.001, UMD = -3.092, 95% CI: -4.092 ± -2.093 bpm). The ES measured through Arena equation was not statistically significantly different from zero (ES = -0.023, 95% CI: -0.174 to 0.070, p = 0.405, UMD = -0.417, 95% CI: -1.407 ± 0.573 bpm). The cumulative effect of four equations (Silva, APMHR, Machado, & Fairbarn) nominated as 'other' was not statistically significantly different from zero (ES = -0.023, 95% CI: -0.475 to 0.428, p = 0.919, UMD = -0.220, 95% CI: -3.709 ± 3.269 bpm). Summary of Sub-group analysis of standardized mean difference along with Heterogeneity statistics (**Table 2**) and unstandardized mean differences (UMD) were presented in **SC 5**.

Table 3 Summary of Univariate Meta-Regression in terms of Continuous and Categorical Moderators

Parameter	Moderator Type	Estimate	Std. Error	t	Sig. (2-tailed)	R^2 %	95% Confidence Interval	
							Lower	Upper
Age	Continuous	-0.01	.2914	.638	.529	0%	-.412	784
BMI	Continuous	.043	.0164	2.631	.015	29.1%	.009	.077
Vo2max	Continuous	-0.032	.0079	-4.033	<.001	46.1%	-.048	-.015
(Participants)	Categorical							
Athletes		-.480	.2155	-2.227	.035		-.137	1.299
Obese		.581	.3492	1.664	.108	41.2%	-.137	1.299
Sedentary								
(Test Type)	Categorical							
Field		-.043	.3449	-.125	.902	0%	-.751	.665
Laboratory								
(Age Group)	Categorical							
Children		-.786	.4589	-1.712	.099		-1.731	.159
Adolescent		-.577	.4352	-1.325	.197	54.6%	-1.473	.320
Adult		-1.286	.3828	-3.358	.003		-2.074	-.497
Older Adult		0	.					

Level of Sig. 0.05

Moderator Analysis

The univariate meta-regression model revealed that in continuous moderators (**See Table 3**), BMI ('t'= 2.631, p < .001), and Vo2max ('t'= -4.033, p < .001) were significant sources of error in the accuracy of estimated and measured MHR. BMI and Vo2max each explained a significant portion of between-study variability (*R^2* values for BMI and Vo2max were 29.1% and 46.1% respectively), while age ('t'= .638, p =529) did not modulate the between-study variability.

In terms of categorical moderators (**See Table 3**), participants were categorized into Athletes ('t'= -2.227, p < .001), Obese ('t'= 1.664, p = .108), and Sedentary (redundant parameter). Athlete participants significantly modulated the accuracy of predicted vs. measured MHR and explained 42.1% portion of attained heterogeneity. Meanwhile, the studies were also categorized on the basis of MHR test type i.e., Field ('t'= -.125, p = .902) vs. laboratory (redundant parameter). The test-type moderator model did not explain the significant variation. Significant variations have been reported through various age categories, children ('t'= -1.712, p = .099), adolescents ('t'= -1.325, p = .197), Adults ('t'= -3.358, p < .001), Older adult (redundant parameter). A total 54.6% portion of between-study variability has been explained by the Age category.

Table 4 Publication Bias Measurement

Test Name	value	p
Fail-Safe N	25.000	0.013
Begg and Mazumdar Rank Correlation	0.069	0.616
Egger's Regression	4.318	< .001
Trim and Fill Number of Studies	0.000	.

Note. Fail-safe N Calculation Using the Rosenthal Approach

Assessment of Publication Bias

Upon visually inspecting our funnel plot (**See Figure 3**), it became evident that there were some noteworthy data points in our sample's effect size distribution that could be potential outliers. Furthermore, we identified signs of publication bias through both the Egger test (with a z-score of 4.318 and a p-value of $< .001$) and the Begg test (with $\tau = 0.069$ and a p-value of 0.616) (**See Table 4**). However, it's important to note that interpreting the results of these tests can be challenging in small-scale meta-analyses characterized by substantial heterogeneity (Higgins & Green, 2008; Sterne et al., 2000).

Discussion

This paper has a primary objective of conducting a thorough and systematic review, along with an in-depth analysis, of the existing evidence pertaining to the accuracy of age-based Maximum Heart Rate (MHR) prediction equations in both male and female children, adolescents, and adults. Notably, this systematic review and subsequent meta-analysis represent a pioneering effort in evaluating the effectiveness of these equations across various studies. In line with contemporary methodological standards, this paper goes beyond conventional approaches. It presents standardized mean differences between predicted and actual MHR values, unstandardized mean differences, and aggregated limits of agreement. Furthermore, the paper offers a quantitative examination of potential influencing factors, such as age, Body Mass Index (BMI), Vo2max, the specific prediction equation employed, and the type of exercise test used.

The quantitative analysis revealed overall small effects (ES = 0.24) between measured and predicted MHR. However, when sub-group analysis was performed in terms of different equations a large effect was shown for the Fox equation (ES = 0.61), and Nes equation (ES = 0.46). while the Londeree equation showed a moderate effect (ES = -0.37). Fox and Nes equations overestimated MHR, while, the Londeree equation significantly underestimated MHR in our sample. On the other hand, Tanaka (ES = 0.13), Gelish (ES = 0.23), Arena (ES = -0.052) equations showed much smaller effect. Similarly, the cumulative effect (ES = -0.023) of five other equations was also small. These outcomes suggest that Tanaka, Gelish and Arena equations predict MHR more accurately and account for more individual variability in our sample than the Fox, Nes, and Londeree equations. A similar meta-analysis (Cicone et al., 2019; Nara, Kumar, Rathee, & Kumar, 2022) included validation of Fox and Tanaka equation reported a large effect size for the Fox equation. The following study concludes that Age-based MHR equations derived from adult populations are not applicable to children. The study recommended the Tanaka equation if the use of age-based equations cannot be avoided (Jangra et al., 2023; D. Kumar et al., 2023; Nara et al., 2023; Nara, Kumar, Rathee, Kumar, et al., 2022). However, pubertal status also influences sympathetic modulation during exercise to facilitate the development of more age-appropriate methods for prescribing exercise intensity.

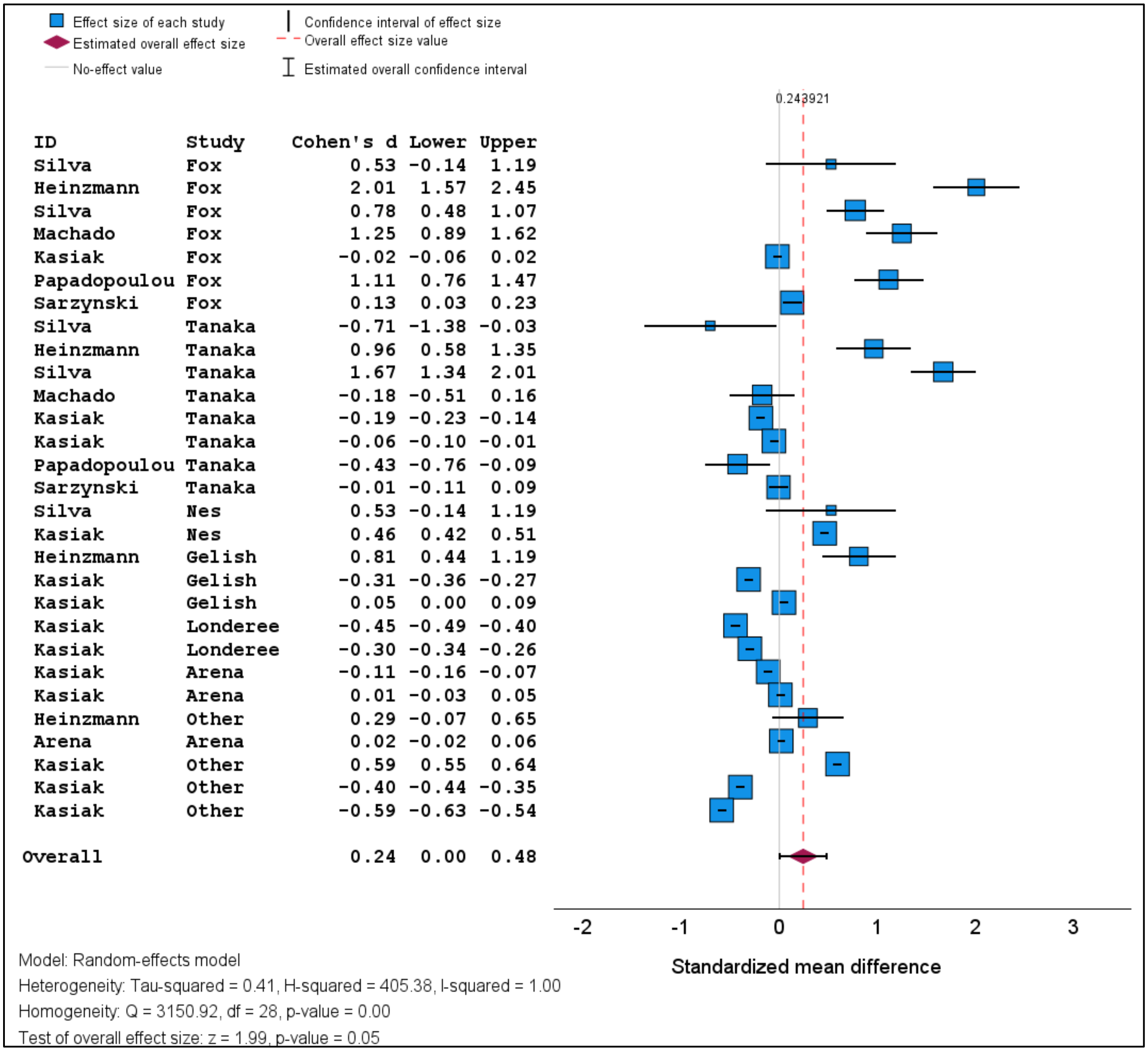

Figure 2. Forest Plot for the 29 effects extracted from the nine studies

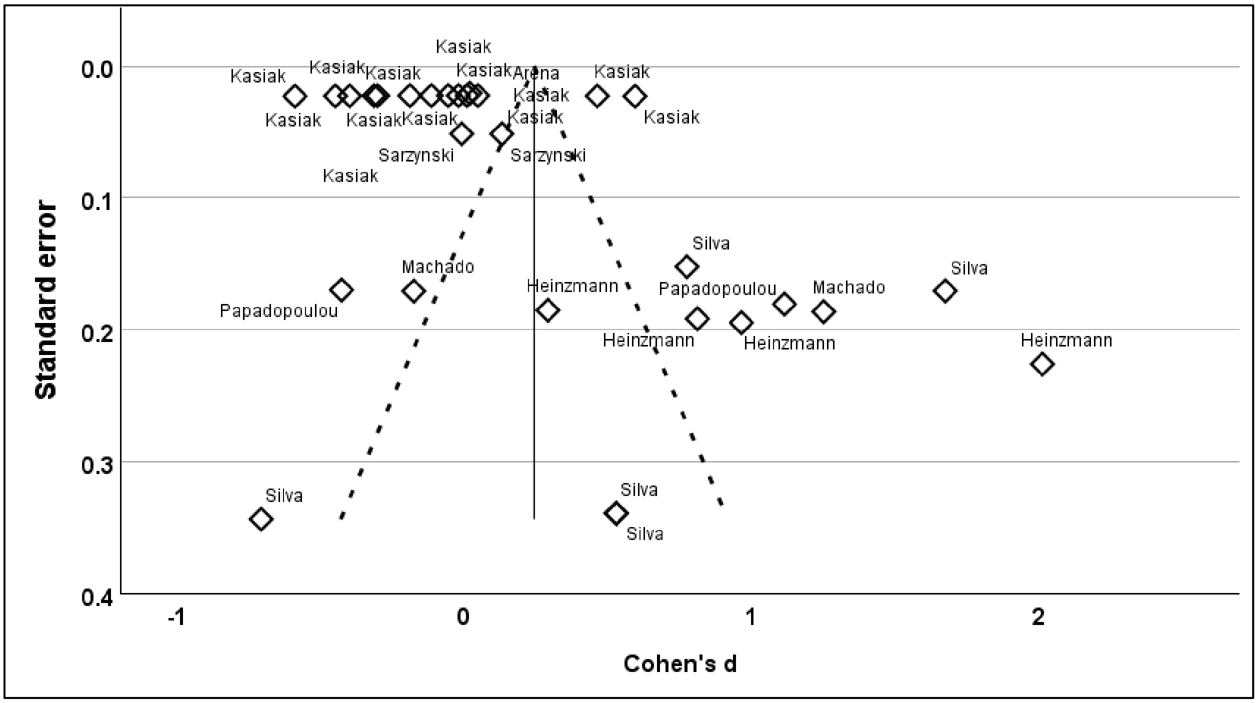

Figure 3. Funnel Plot. The horizontal axis typically represents the effect size estimates of each individual study in terms of Cohen's d effect size (ES). The vertical axis represents a measure of study precision, which is usually the standard error of the effect size. Studies with larger sample sizes or more precise measurements will have smaller standard errors and are therefore plotted higher on the vertical axis.

We examined potential co-variates (moderators, **See SC 5**) that might influence the between-study variability. The chronological age did not modulate the study variability. Age as a continuous moderator did not show significant effects, but age as a categorical moderator showed significant variation in the obtained heterogeneity. The adult age group was revealed as a potential moderator between predicted and measured MHR. The results were similar across children, adolescents, and older adult age groups in our study. The present study suggested that the prediction equation developed on particular age groups is less accurate for different age groups, i.e., the age-based MHR equation developed on children will not produce accurate MHR for the adult population. BMI and Vo2max of the participants also influence the accuracy of the predicted MHR (R^2 = BMI: 29.1%, Vo2max: 46.1%). Therefore, cardiovascular endurance and body composition should be considered during the prediction of MHR.

Another important moderator was identified as the participant's physical activity status (Athlete, Obese, and Sedentary). In the present meta-analysis, the validation of the MHR equations have been done on diverse population. Four studies validate the MHR equation on athletes (Kasiak et al., 2023; Papadopoulou et al., 2019; C. D. Silva et al., 2013), while, another study included Obese individuals (Heinzmann-Filho et al., 2018), and sedentary persons (Sarzynski et al., 2013). We examined the participant's characteristics that significantly modulate the accuracy of prediction equations. Various methods of laboratory-based incremental exercise tests as well as field-based test protocols were adopted by the included studies. No significant variation between different test protocols was observed in predicting MHR. However, in the literature testing environment reported as a potential source of variability, especially testing location and mode of exercise may impact subjects' performance on maximal effort test (WILLIFORD et al., 1999). In our study, testing environment or location and mode of exercise did not influence the accuracy of predicted MHR respectively. Future studies should be designed to determine the influence (if any) testing conditions have on MHR.

Methodological differences present considerable challenges when attempting to characterize how adolescents respond to maximum-effort exercise. More precisely, there is a lack of agreement on what should be considered sufficient secondary criteria for establishing a maximal effort (Armstrong & Welsman, 1994; Washington et al., 1994). Various criteria and standards have been used to quantify the maximum effort (**See SC 4**) in participants including a soccer match (C. D. Silva et al., 2013) with an intensity of 85±3.7% of $MHR_{obtained}$ were used in field settings. Plateau in Vo2max (a stable level of HR or leveling-off in VO_2, defined as an increase < 100 mL·min−1 with growing exercise intensity before exercise test termination) (Kasiak et al., 2023), exhaustion or inability to maintain the required velocity, respiratory coefficient > 1.10, HRmax> 85% of estimated HR (formula: 220-age) were used to estimate maximal effort (Heinzmann-Filho et al., 2018; Karila et al., 2001; Rodrigues et al., 2006). Rating of perceived exertion scale ≥18 and voluntary exhaustion (Arena et al., 2016; Machado & Denadai, 2011; V. A. P. da Silva et al., 2007) reported by the participants during maximal effort. Regrettably, there is a lack of consistent application of these criteria, making it challenging to ascertain whether a genuine maximal effort was achieved. The inconsistent utilization of these testing criteria may contribute to the significant variability observed in effect sizes (*ESs*). The studies especially, used field settings (Papadopoulou et al., 2019; C. D. Silva et al., 2013) have not clearly defined criteria for confirming the attainment of a maximal effort.

While conducting this systematic review and meta-analysis, it's important to acknowledge certain limitations. This type of review can only assess the existing body of research obtained through the search process. Despite our efforts, including reaching out to the original authors for any missing or incomplete data and conducting both electronic and manual searches beyond the university library system, we were restricted to using databases accessible through our institution. Moreover, we intentionally employed broad and inclusive keywords to enhance the sensitivity of our electronic database search. However, it is worth noting that utilizing additional or alternative keywords might have potentially yielded different findings. Additionally, our searches were confined to English-language publications, which could have excluded relevant studies in other languages. Despite these limitations, we have confidence that we identified and included all pertinent peer-reviewed articles that met our predefined criteria in this comprehensive review.

Conclusion

In summary, the Fox and Nes equations overestimated MHR, while the Londeree equation underestimated MHR. The average mean difference and 95% confidence interval of predicted and measured MHR (**See SC 6**) by Fox was 5.60 bpm (1.47±9.73 bpm), Nes equation shows a less mean difference of 1.52 bpm but accounts for more individual variation (-21.25±24.88 bpm). Londeree equation underestimated MHR by-3.09 bpm (-9.57±3.39 bpm). Tanaka, Gelish, and Arena equations represent less mean bias. Out of the three equations, Tanaka's equation accounts for more accuracy and less individual variation. The findings of the study suggested the Tanaka equation as an alternative to other equations as it resulted in less bias between measured and predicted MHR and a reduced range of error.

Second, the study recommends using more robust criteria to determine that a true maximal effort is being attained. Implementing these recommendations could contribute to the standardization of assessments within populations, potentially leading to more accurate guidance in the prescription and monitoring of exercise training intensities for children and adolescents.

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