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# Predicted sweat rates for group water planning in sport: accuracy and application

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**ABSTRACT:** This study tested the accuracy of a novel, limited-availability web application ($H_2Q$™) for predicting sweat rates in a variety of sports using estimates of energy expenditure and air temperature only. The application of predictions for group water planning was investigated for soccer match play. Fourteen open literature studies were identified where group sweat rates were reported (n = 20 group means comprising 230 individual observations from 179 athletes) with fidelity. Sports represented included: walking, cycling, swimming, and soccer match play. The accuracy of $H_2Q$™ sweat rates was tested by comparing to measured group sweat rates using the concordance correlation coefficient (CCC) with 95% confidence interval [CI]. The relative absolute error (RAE) with 95% [CI] was also assessed, whereby the mean absolute error was expressed relative to an acceptance limit of 0.250 L/h. The CCC was 0.98 [0.95, 0.99] and the RAE was 0.449 [0.279, 0.620], indicating that the prediction error was on average 0.112 L/h. The RAE was < 1.0 for 19/20 observations (95%). Drink volumes modeled as a proxy for sweat losses during soccer match play prevented dehydration (< 1% loss of body mass). The $H_2Q$™ web application demonstrated high group sweat prediction accuracy for the variety of sports activities tested. Water planning for soccer match play suggests the feasibility of easily and accurately predicting sweat rates to plan group water needs and promote optimal hydration in training and/or competition.

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## INTRODUCTION

Proper athlete fluid replacement helps optimize training and performance by minimizing problems related to body fluid imbalances [1]. The amount of fluid planned for consumption should be customized on the basis of sweat losses [1], which are the principal determinant of an athlete's fluid needs [2]. Sweat rate (SR) can be gauged by acute changes in body mass (kg) over time, where 1 L = 1 kg [1, 3]. However, while more than 50% of athletes are aware of and understand this recommendation, fewer than 15% practice this strategy [4] and many experience fluid imbalances that can sabotage performance and even health [5, 6]. Furthermore, in both training and competition, the added complexities of fluid availability and drinking opportunities related to the rules of sport make proactive fluid planning a practical reality for many circumstances [5–9]. The accurate prediction of SR would therefore facilitate an unmet need related to optimizing training, performance, and health.

The validity of a patent pending technology ($H_2Q$™) for predicting group runner water needs was recently demonstrated through its incorporation into a commercial water planning tool known as the Road Race Water Planner© (RRWP) app [10]. A limited availability extension of the web application was recently created to predict SR in individual runners using only estimated energy expenditure and air temperature inputs [11]. The web application is accessible for testing (*with permission*) as Application Programming Interface (API) software (i.e., a web page with internal $H_2Q$™ API). A black box engineering interface protects the proprietary algorithm and equations while allowing users full access to prediction functionality. Importantly, the energy required to move one's body mass is different during running when compared to walking, cycling, swimming, or engaging in team sports. Dry heat exchange is also impacted by speed of movement and movement medium (i.e., air vs water). Therefore, sweat prediction equations unique to several sports other than running were incorporated into the $H_2Q$™ algorithm. Although such a tool could be useful, the software algorithm was created purely on theoretical grounds and has unknown accuracy for sports other than running.

This study used a limited availability web application ($H_2Q$™) to examine agreement between SR predictions from a web application ($H_2Q$™) and group measured SR reported in the open literature comprising four popular outdoor sports activities. Close agreement was considered evidence for accuracy and conceptual application to group water planning for sport, which was examined using soccer match play. We also examined the prediction error tolerance to intentional algorithm input errors.

## MATERIALS AND METHODS

We obtained SR data from 14 open literature studies (Table 1) [12–25], which included 20 separate group means, where group sizes ranged from 7 to 27 subjects. One study involved walking, while 5 independent studies looked at cycling, 4 at swimming, and 4 at soccer match play. A total of 230 individual SR observations made up the 20 group means. Of the 179 subjects studied, 143 were male and 36 were female. The caliber of participants ranged from recreational [12] to elite [25]. Swimming was performed using indoor pools; all other exercise was performed outdoors in real-world conditions or in a laboratory with airflow designed to simulate natural over-ground convection (i.e., movement velocity) [14]. Table 1 provides selected study details. A search of the open literature was made using PubMed, SPORTDiscus, and Google Scholar databases. Cross referencing of eligible studies was also used. To be eligible for inclusion, studies needed to have measured SR outdoors using careful laboratory techniques [3] with a minimum correction for fluid ingestion and urine excretion (where appropriate). One study provided corrections for respiratory water loss and $CO_2$–$O_2$ exchange (i.e., non-sweat losses of body mass) [15]; the remaining 12 studies were corrected herein for non-sweat losses of body mass using energy expenditure within the formula: whole body sweat loss = measured change in body mass – 0.20 g per kcal energy expenditure [2]. Finally, studies had to provide air – or water – temperature, body mass, exercise duration and distance (with the exception of soccer – see below).

Energy expenditure (kcal) for walking and swimming were computed as the product of body mass (kg), exercise distance (km) and the modality-unique energy cost coefficient for each [26, 27]. The same approach was used for cycling [28], but in addition the equation and assumptions of Martin et al. [29] were tested for comparison, whereby speed was calculated (distance/time) and bike mass was set to 10 kg. Energy expenditure for soccer match play is not yet fully resolved. It is certainly above that measured for ordinary running [30], but even the most sophisticated attempts at measurement acknowledge under-estimating the true value [31].

**TABLE 1.** Research studies included in $H_2Q$™ group sweat rate predictions

| Authors | Sport | Group Size (n) | Air Temp. (°C) | Energy Cost (kcal) | Exercise Time (min) | RAE (ratio) |
|---|---|---|---|---|---|---|
| O'Neal et al. [12] | Walk | 27[c] | 25.8[f] | 313 | 60.0 | 0.212 |
| Brown and Banister [13][a] | Cycle | 7 | 15.0 | 1352 | 93.2 | 0.036 |
| Saunders et al. [14][b] | Cycle | 9 | 33.0 | 1557 | 116.7 | 0.660 |
| Fox and Burns [15] | Cycle | 9 | 27.9 | 1210 | 69.7 | 0.260 |
| Mieras et al. [16][a] | Cycle | 12 | 22.1 | 1442 | 83.0 | 0.050 |
| Racinais et al. [17] | Cycle | 9 | 36.0 | 1259 | 77.3 | 0.236 |
| | | 9 | 37.4 | 1237 | 69.4 | 0.104 |
| | | 9 | 36.2 | 1227 | 65.6 | 0.312 |
| Lemon et al. [18] | Swim | 8[d] | 26.6[g] | 1212 | 62.0 | 0.740 |
| Soler et al. [19] | Swim | 9 | 26.8[g] | 2635 | 158.0 | 0.896 |
| Maughan et al. [20] | Swim | 9 | 27.4[g] | 1560 | 105.0 | 0.248 |
| | | 8[e] | 27.4[g] | 1280 | 105.0 | 0.088 |
| Macaluso et al. [21] | Swim | 9 | 26.8[g] | 1454 | 75.7 | 1.312[h] |
| Kurdak et al. [22] | Soccer | 11 | 34.3 | 1145 | 90.0 | 0.272 |
| | | 11 | 34.3 | 1068 | 90.0 | 0.672 |
| | | 11 | 34.3 | 1156 | 90.0 | 0.036 |
| | | 11 | 34.3 | 1078 | 90.0 | 0.416 |
| Guttierres et al. [23] | Soccer | 20 | 29.0 | 1150 | 90.0 | 0.776 |
| Da Silva et al. [24] | Soccer | 15 | 31.0 | 1066 | 90.0 | 0.948 |
| Mohr et al. [25] | Soccer | 17 | 21.0 | 1298 | 90.0 | 0.704 |

[a]Outdoor trial only; [b]Trial where air velocity equals calculated road speed (100WS); [c]all females; [d]1 female; [e]8 female; [f]Wet Bulb Globe Temperature input as air temperature; [g]Water temperature; [h]Prediction error greater than allowable error (0.250 L/h); i.e., RAE > 1.0, where RAE is the relative absolute error (i.e., absolute error/0.250; see text)

A pilot study using 71 youth soccer players was performed where SR and air temperature were measured and running distance was captured using GPS during training sessions (investigator LBB, unpublished). A theoretical heat balance platform from a running model [11] was modified for match play and the necessary energy expenditure required to elicit the measured SR in soccer was solved for by algebraic re-arrangement using heat balance biophysics (investigator SNC, unpublished). Briefly, a heat balance equation of the form: [M – W – (R + C) – E = S] was rearranged to: M = S + E + (R + C) + W, where a measured volume of sweat is converted to evaporative heat loss (E), dry heat loss (R + C) and work (W) are carefully estimated, and heat storage (S) is ignored as heat balance is assumed to be steady-state. M heat energy can then be expressed in kcal units and in relation to body mass and running distance. A best fit energy cost coefficient was then determined and applied to correct SR for non-sweat losses of body mass during published soccer play (Table 1) and to iteratively estimate a corrected total energy expenditure for $H_2Q$™ predictions. Because running distance was not a measured outcome in soccer match-play studies reporting SR (Table 1), distance was uniformly estimated as 10 km [31, 32] for the 90 minute matches.

Sweat predictions were made by inserting energy expenditure and air – or water – temperature inputs from the 14 studies into the proprietary $H_2Q$™ algorithm (performed by investigator SNC). The generalized $H_2Q$™ formula is: ($m$ × (air temperature, ºC) + $b$) × (energy expenditure, kcal) = sweat loss (mL), which divided by time gives SR. Slope ($m$) and intercept ($b$) terms will be unique for individuals when experimentally derived by measurement across a variety of energy expenditure and air temperature combinations. Therefore, rational and empirical biophysical equations and well-characterized physiological equations were concatenated and used instead to simulate a small universe of conditions from which best fit $m$ and $b$ parameters were estimated to make one unifying and proprietary equation for each sport. All calculations were performed by investigator SNC. To allow for an independent validation of the prediction outputs, a web-based application was created using black box engineering (Sequoia Applied Technologies, Inc., Sunnyvale, CA, USA) to obscure the proprietary equation elements while retaining input-output functionality (i.e., requires only two inputs). Investigator KJS was provided web account access and applied the same energy expenditure and air – or water – temperature inputs. All 20 sweating predictions were the same to within ≤ 2 mL/h (rounding error only) between investigators. Therefore, independent validation of $H_2Q$™ prediction fidelity could be achieved without disclosing the proprietary algorithm or sport-specific best fit $m$ and $b$ equation parameters.

Sweat prediction accuracy was assessed by quantitative agreement between predicted and measured SR using the concordance correlation coefficient (CCC), which measures the degree of departure between predicted and measured values relative to perfect concordance, or line of identity, rather than the best fit line of prediction (i.e., ordinary regression) [34]. Therefore, the CCC uniquely affords quantitative accuracy describing departure from perfect 45º agreement. A minimum of between 10 and 20 data pairs is recommended for use with the CCC [34], thus a plot of 20 data pairs was considered adequate for meaningful results interpretation. A CCC > 0.80 is considered very good agreement [35], particularly given that the x-axis was itself an imperfect gold standard. Since neither x nor y axes were free of error, the ratio of the absolute prediction error (L/h) [36] to a standard reference (0.250 L/h) (i.e., relative absolute error (RAE))) was also computed, whereby values < 1.0 are most desirable [37]. The 0.250 L/h reference value was selected based on acceptable accumulation error in total body water (± 1 to 2%) during prolonged running (≥ 4 hours) [10]. However, for the mean duration of exercise in Table 1, which was ~1.5 hours, ± 0.250 L/h error would accumulate to even smaller (< 1%) changes in body water (surplus or surfeit). Qualitative agreement was also examined by the percentage of predictions falling below the 1.0 RAE threshold. Lin's CCC was calculated using published equations [34] integrated within Microsoft® Excel, 2013. All other statistical and graphical work was completed using GraphPad Prism version 8.0 (GraphPad Software, La Jolla California USA, www.graphpad.com).

## RESULTS

The range of study air temperatures (15 to 37.4ºC) and water temperatures (26.6 to 27.4ºC), as well as the range of exercise durations (60 to 158 minutes), are provided in Table 1. Fig. 1 (A-D) provides plots of predicted (y-axis) versus measured (x-axis) SR. The values on the x-axis have been corrected for non-sweat losses of body mass, but still contain some error inherent to the techniques used [3]. Energy expenditure in Fig. 1B was calculated using the equations of [29], whereas 1B2 (inset) were calculated using mass, distance, and the energy cost coefficient for cycling [28]. The former was used in Fig. 2 as it provided a closer fit with the line of identity. Because CCC requires a minimum of 10 data pairs for analysis, Fig. 2 was created as an analytical composite to validate prediction accuracy across sports. The CCC in Fig. 2 was 0.98 with a 95% confidence interval of [0.95, 0.99]. The mean RAE was 0.449 with a 95% confidence interval of [0.279, 0.620]. This indicates that group SR predictions were, on average, 55% smaller than the *a priori* error acceptance threshold (± 0.250 L/h), or ~0.112 L/h (less than 4 fluid ounces per hour). All but one RAE value was < 1.0 (Table 1), thus 19/20 group SR predictions, or 95% of group predictions, met the RAE accuracy criteria.

In an effort to understand how the accuracy of inputs themselves potentially impact SR prediction accuracy, ± 10% errors were systematically applied to air temperature and energy expenditure inputs. When inputs were decreased or increased by 10%, SR predictions were naturally reduced or increased, respectively. For -10%, the RAE increased from 0.112 L/h to 0.300 L/h (above the acceptance 0.250 L/h threshold) and the CCC was 0.89 [0.78, 0.94], the lower bound of the CCC confidence interval falling below 0.80. For +10%, the RAE r was 0.285 L/h (above the 0.250 L/h acceptance threshold)

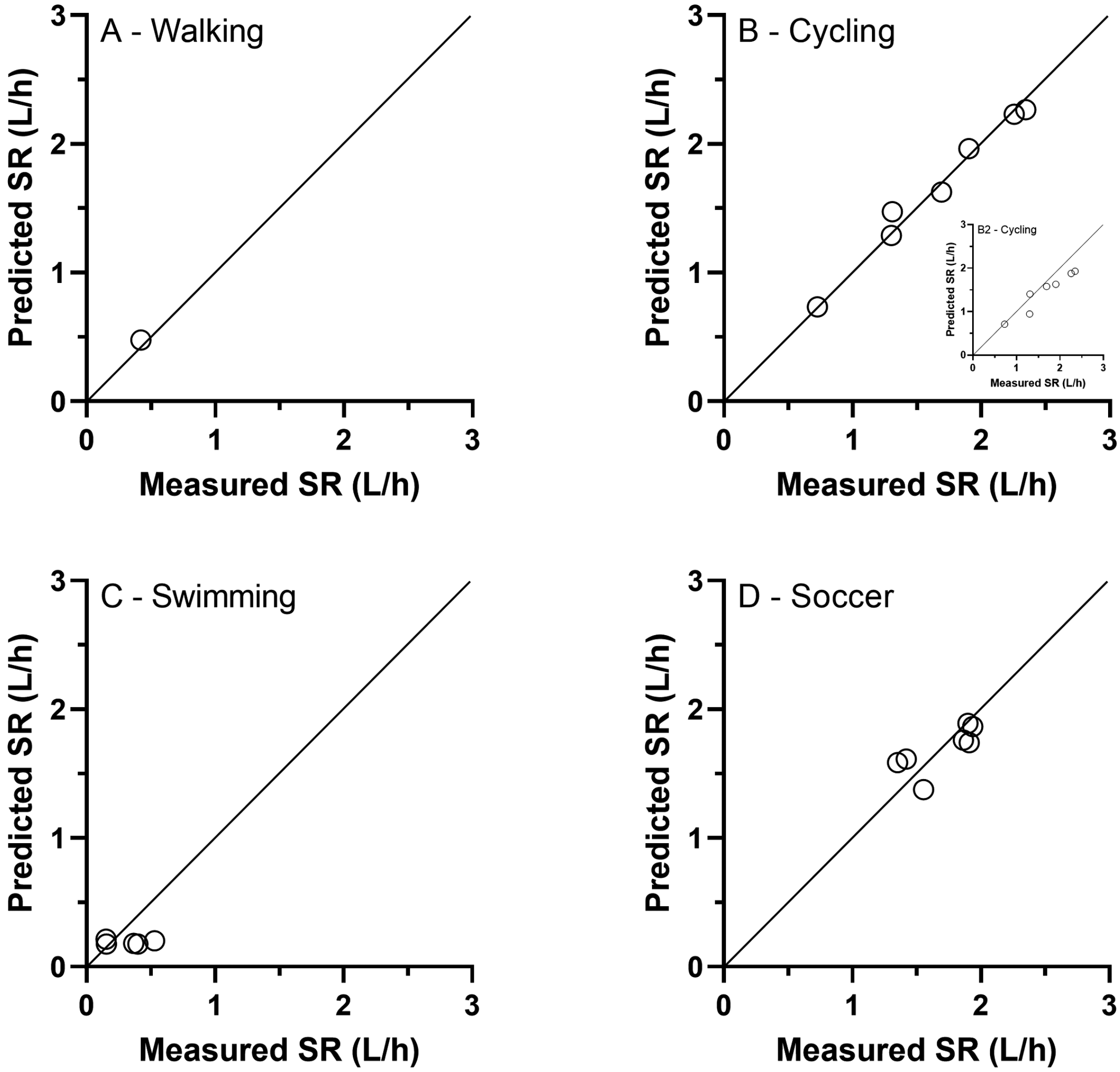


**FIG. 1** Regression plots of predicted (y) versus measured (x) SR in walking (A), cycling (B), swimming (C) and soccer match play (D). Figures B and B2 (inset) used two different energy expenditure calculations (see text). Solid diagonal line represents perfect concordance (line of identity).

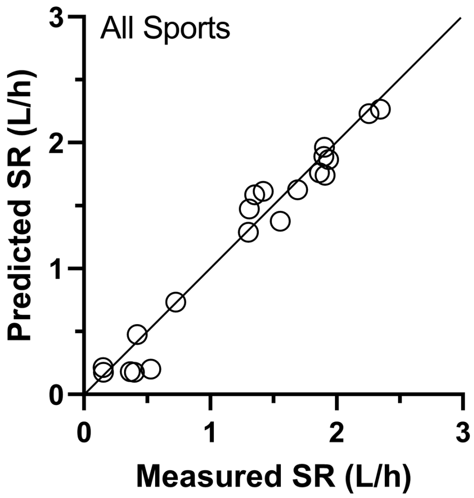


**FIG. 2** Composite regression plot of predicted (y) versus measured (x) SR for walking, cycling, swimming, and soccer match play (all sports). Solid diagonal line represents perfect concordance (line of identity). CCC = 0.98 [0.95, 0.99].

and the CCC was 0.94 [0.86, 0.97], the lower bound of the CCC confidence interval >0.80.

To examine the feasibility of using $H_2Q$™ predictions to plan drinking for soccer match play, the group mean SR prediction for each soccer match play study [22–25] was extrapolated to 90 minutes and net dehydration was calculated as a percentage change in body mass due to sweat losses (% dehydration) using three theoretical drinking strategies (Fig. 3A-C). Fig. 3A illustrates conceptually how drinking no fluid before each half of a soccer match would impact dehydration. Fig. 3B shows the relative improvement in hydration achieved by a strategy of consuming a standardized 250 mL volume of fluid before each half [38]. Although adopting a 2 × 250 mL strategy (Fig. 3B) reduced the absolute amount of dehydration compared with Fig. 3A, in all 7 examples dehydration accumulated to > 2% body mass, which

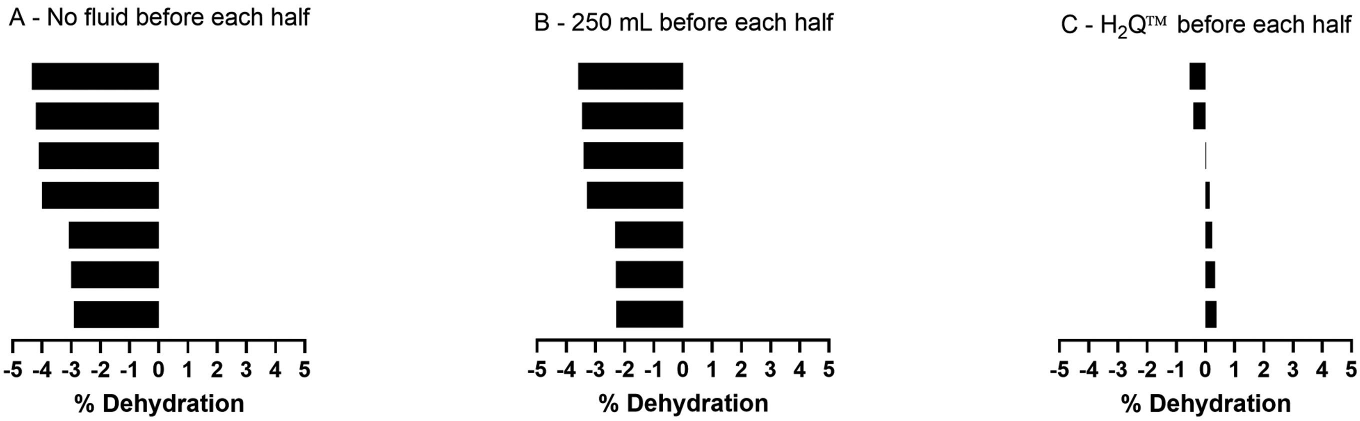


**FIG. 3** Group water planning illustrating the effects of prescribing no fluids (A), 250 mL of fluid before each half (B) [38], or $H_2Q$™ predicted fluid volumes divided equally before each half of soccer match play (C) on the development of dehydration by match end (90 minutes). Each bar represents a group mean from the studies cited for soccer match play in Table 1.

would exacerbate strain and contribute to performance impairment [6, 39]. In Fig. 3C, $H_2Q$™ predictions were divided equally into two parts, following the same strategy as in Fig. 3B. Planning and consuming $H_2Q$™ provisions resulted in superior fluid balance by closely matching fluid intakes to sweat losses (Fig. 3C), but single fluid boluses ranging from 900 mL to 1400 mL were required, which might be impractical. Importantly, the more realistic consumption of even half the predicted volumes (450 mL to 700 mL) would still lead to minimal changes in fluid balance (± 1% body mass change).

## DISCUSSION

This study used a limited availability web application ($H_2Q$™) to predict SR for comparison to measured SR in 20 groups of athletes representing 4 different sports cohorts. Results indicate that $H_2Q$™ predictions were in excellent agreement with measured SR. These outcomes suggest the strong feasibility for using SR predictions for group water planning to promote optimal hydration in training and/or competition for the variety of sports examined.

SR predictions were accurate (CCC, RAE) with group errors that were 55% smaller than the *a priori* error acceptance threshold. While it is easier to predict SR for groups than for individuals [40], $H_2Q$™ has been shown accurate for both groups and individual runners [10, 11]. It is highly plausible that the accuracy of group predictions in this study will remain accurate when applied toward individual SR predictions for exercise and sports such as walking, cycling, swimming, and soccer, but only an experimental test will confirm or refute this hypothesis.

The SR prediction accuracy achieved from just two inputs across a wide range of air temperatures is consistent with the known contributions of energy expenditure and air temperature to sweating [41]. The requirement for evaporative cooling ($E_{req}$) has been carefully and quantitatively described to explain as much as 90% of the variance in SR during controlled indoor exercise [42] and as much as 78% under much more variable conditions [43]. The basic components of $E_{req}$ reduce to energy expenditure (M – W) and air temperature influences on dry heat exchange (R+C). Other factors commonly implicated in affecting SR, such as sex, age, fitness, and others, are intuitively part of the SR measurement, thus any contribution they make to prediction error is already bundled in the small, total agreement error reported herein. Existing SR prediction models [44, 45] do not easily lend themselves to adoption within sports due to their required input complexity and lack of extension validity [46]. The non-obviousness of an algorithm that can generate high accuracy for sports from just two inputs is what makes the generalized equation constants proprietary.

Energy expenditure can be estimated using various combinations of accelerometry, heart rate, and GPS tracking [47]. In this study, energy expenditure was computed from commonly available equations relating mass and distance or speed with modality-unique energy cost coefficients. Although the accuracy of these estimates can be challenged, SR prediction results were excellent and $H_2Q$™ relies heavily on the assumption of energy expenditure accuracy [11]. In practice, modality-unique energy cost coefficients combined with scale (body mass) and GPS-enabled distance tracking (km) may be all that is necessary for enabling highly accurate energy expenditure estimates [11]. Indeed, with algebraic substitution techniques, simple inputs are possible. For example, accurate group water planning for runners can be achieved with knowledge of only race distance, number of race participants, and air temperature [10]. Similarly, knowledge of player body mass and air temperature alone (distance fixed at 10 km) permits estimates of *a priori* energy expenditure, thus the sweat losses in Figure 3 could be estimated accurately in advance for pre- and mid-match drink planning by using a simple matrix of body masses and air temperatures. The measurement methods for reported air temperature in the 14 studies examined varied or were not disclosed. Fortunately, air temperature can be accurately estimated, even at considerable distances from a location [48], using any number of common mobile weather app providers that pool data from nearby meteorological stations. Clearly, the fidelity by which energy expenditure and air temperature were estimated for use within the $H_2Q$™ algorithm were sufficient to produce accurate SR predictions for small groups of athletes. However, input errors should be < 10% for accuracy to remain high. The manipulation of input error is an exercise which underscores the intuitive need for accurate inputs. In practical terms, the methods described above appear highly feasible as they worked very well as applied herein, but occasional common sense checks against SR measured by body mass change [3] is always prudent in practice.

Like any algorithm, $H_2Q$™ contains parameter limits (i.e., domain of validity; DOV) on environment and movement velocity, which excluded the use of some studies from the literature. For example, only 1/3 trials from Macaluso et al. [21] (Table 1) were used in this study because 2 of the trials were in water temperatures outside Fédération Internationale de Natation water temperature guidelines (DOV: 26 to 28ºC). Similarly, only 1 of 2 trials was used from Mohr et al. [25] (Table 1) because 1 trial exceeded the modeled air temperature limit (DOV: 10 to 40ºC). A small number of other potentially eligible studies were excluded on similar grounds for swimming (n = 1 study) and soccer (n = 3 studies).

Several excellent studies of SR and sweat electrolyte composition in soccer were also excluded because players were studied during practice or training, rather than genuine match play, or exercise duration was well above or below 90 min (n = 9 studies). Under these conditions, the distance covered may be quite different from the 10 km assumption [32, 33, 49]. For example, Duffield et al. [50] measured SR, air temperature, and distance covered (GPS) during a simulated soccer match. They reported a distance of 7.558 km over 100 minutes. The use of 10 km over 90 minutes gives a SR prediction of 1.61 L/h. However, the more precise substitution of 7.558 km and 100 minutes into $H_2Q$™ gives a prediction of 1.094 L/h. When the SR reported by Duffield et al. [50] (1.33 L/h) is corrected using calculated energy expenditure, the corrected SR is 1.219 L/h. The difference between the predicted and measured (after correction) SR using estimated time and distance was 0.391 L/h (RAE 1.56); the difference using precise time and distance was 0.125 L/h (RAE 0.50). Therefore, it is likely that improved accuracy of true match play distance covered, or possibly assignment of different distances according to player position [31, 49], could further improve SR accuracy beyond the excellent group results already achieved using uniform 10 km and 90 minute match play assumptions (Fig. 3C). Until distance covered during match play becomes commonly and reliably available, a 10 km assumption works well for predicting SR for groups (i.e., teams), but only during match play.

## CONCLUSIONS

This study used a limited availability web application ($H_2Q$™) to assess if SR could be accurately predicted in groups of athletes in 4 different sports, comprising various exercise durations in a wide range of environments. The results indicate prediction accuracy sufficient to be used for endurance sports and soccer group water planning to promote optimal hydration in training and/or competition (e.g., Figure 3). Our findings illustrate strong proof-of-concept for group sport water planning from SR predictions. Future studies that prospectively test the accuracy of $H_2Q$™ for group water planning are recommended, including large-scale indoor training environments that simulate realistic outdoor activities. Validation studies using $H_2Q$™ to predict SR for individuals in the 4 sports examined herein is also of interest.

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### Conflict of interest

Author SNC is the owner of Sports Science Synergy, LLC and creator of the $H_2Q$™ web application (patent pending). Author LBB is employed by PepsiCo, Inc. The soccer pilot study was funded by the Gatorade Sports Science Institute, a division of PepsiCo, Inc. The views expressed in this article are those of the authors and do not necessarily reflect the position or policy of PepsiCo, Inc.

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