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# Beyond Generic Calculators: An Integrated, Adaptive Methodology for Estimating Caloric Needs in Resistance-Trained Individuals

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## ABSTRACT

Most widespread fitness calculators calculate basal metabolic rate (BMR) using total body weight, use fixed deficit/surplus amounts, employ a fixed thermic effect of food (TEF) regardless of macronutrient breakdown, and do not account for training experience. This ubiquitous methodology largely differs from what the exercise-science literature currently supports, especially for resistance-trained individuals, whose body compositions differ most substantially from population averages. This review considers four domains where the existing literature supports a more individualized methodology: BMR formula calculation based on body composition as well as total mass, caloric requirements scaled with training phase and experience, macronutrient partitioning based on evidence-based floors and ideal ranges, and performing iterative calculations to account for the thermic effect of food based on macronutrient breakdown. Additionally, due to the large genetic variation and metabolic regulation, an adaptive approach in which total caloric targets/macronutrient breakdown are recalibrated periodically is critical for the most accurate estimates and best results. Future studies should directly compare the integrated and adaptive methodology presented in this paper with generic calculators and measure changes in body composition to validate their effectiveness.

## INTRODUCTION

At 13, like many teenage boys, I wanted to get big and strong. I wanted to bulk up and put on as much muscle as possible. So, I went to a standard calorie calculator, entered in my age, weight, height, sex, and activity level, and was told my maintenance was about 2200 calories. Accordingly, in order to gain weight, it gave me my "perfect" number: 2700 calories. This was great. It was my first time tracking my calories and taking my fitness seriously. Within a week, I was starving all the time. Within a month, I had lost a substantial amount of weight, but I told myself the website was right and that this was just a blip. But as more time passed, I got skinnier and skinnier, until two months in, I began questioning how this was even possible. How could this calculator be so far off? This was the moment my obsessive journey into the depths of the fitness industry and its misinformation began.

However, I was far from the only one facing this problem. With fitness becoming increasingly popular in the 21st century, there are more fitness tools than ever before. Popular health platforms, including Healthline and Mayo Clinic, offer personalized calorie targets that account for your weight, height, age, and activity level, whether you want to lose fat, maintain your weight, or build muscle. Yet these estimates fail to account for the ever-expanding exercise science literature, which suggests that many more factors are at play in determining someone's caloric needs. These factors include: body composition, macronutrient distribution, training phase, and training experience. While these generic estimates may be somewhat applicable to the larger public, the people most likely to seek precise nutritional guidance are those who actively resistance train and fitness enthusiasts who are most likely to actually follow structured, precise nutritional planning. This review examines four key ways in which the current literature calls for a more in depth approach than current tools offer, one that accounts for basal metabolic rate (BMR) formulas, which factor in lean mass, not only total weight, the thermic effect of food (TEF) as a factor of macronutrient breakdown, varying caloric requirements depending on muscle gain, fat loss, or maintenance, and training experience level, and personalized macronutrient breakdown. Considering all of these variables, they make a compelling case for a more integrated and personalized methodology for calculating one's true daily caloric needs—one that current fitness tools fail to offer. When calculating total caloric expenditure, and therefore determining how many calories someone needs to put on muscle, lose fat, or maintain weight, there are four factors to consider: basal metabolic rate (BMR), how many are burned completely at rest per day through bodily functions such as maintaining core body temperature; non-exercise activity thermogenesis (NEAT), how many calories are burned through activity such as walking, fidgeting, typing, etc.; exercise activity thermogenesis (EAT), how many calories a day are burned through direct exercise such as weightlifting, running, biking, etc.; and thermic effect of food (TEF), which accounts for calories burned digesting food. When added all together, we get someone's total daily energy expenditure (TDEE), which we can then use to accurately determine how many calories someone needs to consume in any given day.

## METHODOLOGY

The sources used in this review consist of peer-reviewed studies, meta-analyses, and systematic reviews, along with a small number of practitioner frameworks when peer-reviewed data were not available. Most of these sources were located through Google Scholar and PubMed. Priority was given to the highest-quality evidence available, favoring larger studies and meta-analyses conducted under controlled conditions, while practitioner frameworks were included only where necessary, with their limitations explicitly stated. This is a narrative review rather than a systematic one, and so does not follow formal inclusion and exclusion criteria. This review uses basal metabolic rate (BMR) and resting metabolic rate (RMR) interchangeably, as the cited literature often does.

## SECTION 1: BMR FORMULA ACCURACY AND THE CASE FOR LEAN MASS

Standard formulas used to calculate BMR all use the same factors, with slightly different formulas. These factors include height, weight, age, and sex. Take the Mifflin-St Jeor formula, the current clinical standard recommendation by the American Dietetic Association:

```
Men: BMR = (10 × weight kg) + (6.25 × height cm) − (5 × age) + 5
Women: BMR = (10 × weight kg) + (6.25 × height cm) − (5 × age) −
161
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For most non-obese adults, this formula achieves a 70-82% ±10% accuracy (Mifflin et al., 1990; Frankenfield et al., 2005). Other popular formulas, including Harris-Benedict (Roza & Shizgal, 1984) and Cunningham (Cunningham, 1980), all share a foundational assumption: total body weight alone is sufficient to determine BMR, without distinguishing between total lean and fat mass. For average populations, these methods work quite well, but for more muscular individuals, these formulas are less accurate. In a meta-analysis of 29 studies and 1,430 athletic and resistance-trained participants, most formulas predicted BMR within ±10% with only 40.7-63.7% accuracy, substantially worse than general population performance (O'Neill et al., 2023).

These less-accurate results make mechanistic sense when considering the variance in the energy requirements of muscle and fat tissue. Muscle tissue burns approximately 13 kcal per kg per day, whereas fat tissue only burns 4.5 kcal per kg per day (Wang et al., 2010). For example, two men both weighing 180 pounds but with very different body fat percentages — one at 25% body fat that carries 135 lbs lean mass and one at 12% that carries 158 lbs lean mass — would, on average, have a very different BMR, as one has 23 pounds more of metabolically active tissue. However, it is worth noting that the most accurate formula, the Ten Haaf (ten Haaf & Weijs, 2014), achieved a precision of 80.2% even though it failed to account for lean mass, likely indicating that it is better calibrated to more athletic populations rather than universally more accurate (O'Neill et al., 2023). The literature supports using different formulas for different populations, scaled by lean-to-fat mass ratios. For individuals with reliable body composition measurements, the data theoretically supports formulas that account for lean mass vs. fat mass and scale accordingly. Although we do not have one exceptional universal formula, the most accurate formula is the one that best suits the population.

## SECTION 2: CALORIC REQUIREMENTS ACROSS TRAINING PHASES

Generic TDEE calculators use a one-size-fits-all approach for fat loss, recomposition, or muscle gain, simply taking your maintenance calories and adding/subtracting a fixed amount. However, the literature does not support this approach and instead argues for a more nuanced and adaptive one.

When in a surplus, the size of the surplus, the trainee's rate of gain/loss, and the trainee's experience all determine how much of the weight gained is lean versus fat mass; in a deficit, they determine how much of the weight lost is muscle or fat tissue. A study of 28 resistance-trained participants across the span of 6 weeks found that at a rate of gain of 0.55% of total body weight per week, a significant majority of that mass gained was muscle tissue; however it is worth noting that although every participant followed the same program, their results varied dramatically (how much muscle versus fat tissue they gained), such that the study could only explain 18-40% of the variance between participants (Smith et al., 2021). This is worth acknowledging because it suggests that everyone responds differently to the same plan, calling for a more adaptive approach that will be covered later. Additionally, a controlled resistance training study examining the relationship between surplus size and muscle growth found that faster rates of weight gain (a larger surplus) tended to produce more fat gain as well on average, suggesting that past a certain rate of weight gain, rates of muscle growth diminish and that extra weight is stored as fat, suggesting that a moderate surplus is ideal for optimizing the ratio of muscle to fat gain (Helms et al., 2023). However, the optimal number of surplus calories largely depends on the trainee's ability to build muscle. One's ability to build muscle depends largely on one's genetics and gym experience. While direct peer-reviewed data establishing these specific results are limited, practitioner frameworks suggest that, on average, beginners can gain between 15 and 25 pounds of muscle per year, depending on their genetics and training consistency (McDonald, n.d.). They found that the rate of possible muscle gain quickly slows, with intermediates able to gain 6-12 pounds of muscle per year and advanced trainees only 2-4 pounds per year. We know that larger surpluses up to a certain point should provide more muscle gain, so we can infer that beginners could benefit from larger surpluses than advanced trainees, suggesting that a one-size-fits-all approach to ideal caloric surpluses could, in some cases, limit how much muscle one could gain, and in others, cause excess and unnecessary fat gain. However, this claim is purely a logical inference and has not been conclusively validated through controlled trials.

The same question arises for the optimal caloric deficit. A meta-analysis examining how the size of a caloric deficit affects the ratio of muscle/fat loss found that up to a deficit of 500 calories, lean mass loss was largely prevented (Murphy & Koehler, 2022). Anything less, and the rate of fat loss is not optimized; anything more, you risk losing muscle in the process. However, it is important to consider the 500-calorie threshold as an average number, and not necessarily accurate for everyone. This approach again is not uniform, as we know that beginners, on average, have a greater capacity to grow muscle, and could theoretically be able to build significant amounts of muscle, even when in a deficit, whereas advanced trainees would likely not be able to, suggesting that the ideal deficit size varies widely based on experience level.

Moreover, it is important to consider metabolic regulation. A study of 109 individuals eating in a 25% calorie deficit over the course of 11 months noticed an average decrease of their resting metabolic rate (RMR) of 101 calories, with 40% of that reduction not attributable to changes in body composition/weight alone (Martin et al., 2022). Given this data, we can see that the principle of metabolic downregulation compounds over time and in order to maintain the same caloric deficit you were once in, it may be critical to further drop calories to account for these effects. A more extreme example of this principle can be seen in a longitudinal study following participants in the game show, The Biggest Loser. During the 30 weeks, contestants lost an average of 128 pounds each and saw a staggering drop to their BMR of an average of 610 calories (Fothergill et al., 2016). However, this regulation does not always occur. For example, in a 6-week study, where resistance-trained women ate around 25% below their maintenance calories, there was no measurable drop to their BMR, showing that this regulation takes time to occur (Siedler et al., 2023).

## SECTION 3: MACRONUTRIENT PARTITIONING: PROTEIN, FAT, AND CARBOHYDRATE TARGETS

Caloric intake determines the direction your weight will move, but by optimizing macro ratios—protein, carbs, and fats—you can further optimize results to protect against muscle loss in a caloric deficit or increase the proportion of muscle growth in a surplus. Generic calculators are, therefore, incomplete because they fail to account for these factors. The literature has identified evidence-based ratios of protein, carbs, and fats to optimize body composition.

The most critical macronutrient to consume adequate amounts of is protein; protein is essential for the rebuilding of muscle tissue from weight training. However, the most widespread ideal protein target of 1.6-2.2g/kg of body weight is not necessarily true and depends heavily on your body composition and training stage. A systematic review examining protein requirements during a caloric deficit found that optimal protein intakes scaled up to 2.3-3.1g/kg of lean mass, increasing with both the size of the deficit and the leanness of the trainee (Helms et al., 2014). For example, someone with 8% body fat who is losing 2% of their body weight per week could benefit from the higher end, whereas someone with substantially more body fat who is losing weight more slowly could get away with the lower end. Additionally, a separate meta-analysis examining optimal protein intake during a caloric surplus found that extra lean mass gains were capped at 1.62g/kg of body weight, establishing a protein ceiling in which additional intake provides no further benefit for muscle gains (Morton et al., 2018). Protein requirements are not fixed; they depend heavily on the training phase being run. During heavy caloric deficits, lean individuals require more protein than traditionally recommended, whereas individuals in a caloric surplus would see no additional benefit beyond the low end of the traditional recommendation.

Sufficient fat intake is also critical for optimal body composition. A meta-analysis of 6 controlled intervention studies found that low-fat diets, of at or below 20% of total caloric intake, produced a 10-15% reduction in testosterone in men, compared to high-fat diets, of approximately 40% of total caloric intake coming from fats (Whittaker & Wu, 2021). While we cannot directly determine an exact minimum threshold for fat intake, we can infer that the ideal range is above 20% of daily caloric intake.

Carbohydrates are crucial for maximal output in hypertrophic training. An analysis of a high-intensity set of bicep curls found that approximately 80% of the energy produced comes from glycolysis, the metabolic process in which carbohydrates are converted into ATP (Lambert & Flynn, 2002). However, the importance of carbohydrates caps at a certain point; research comparing carbohydrate intakes of 0.37g/kg of body weight and 7.66g/kg of body weight over the span of 48 hours found no difference in total training output across 15 sets between the two groups (Mitchell et al., 1997). However, a broader systematic review found a case for implementing a higher-carb diet in higher-volume training protocols exceeding 10 sets per muscle group per session, suggesting that the true threshold for carbohydrate intake is not a uniform number (Henselmans et al., 2022). However, for most resistance-trained individuals, as long as protein intake is adequate, fat intake is above 20% of daily intake, and carbohydrate intake is moderate, results should be optimized in terms of macronutrient composition.

## SECTION 4: THE THERMIC EFFECT OF FOOD AND ITS ROLE IN CALORIC CALCULATION

Beyond typical estimations for someone's maintenance calories lies a factor that is often overlooked: the thermic effect of food (TEF) — the amount of calories burned through the digestion of food. Standard calculators often assign a fixed value for this number to roughly 10% of total calories consumed (de Jonge & Bray, 1997).

The thermic effect of food is not uniform across the three main macronutrients — proteins, carbs, and fats — and each macronutrient burns a certain percentage of its calories through digestion (Westerterp-Plantenga et al., 2009; Tappy, 1996). Here are the widely accepted ratios for the following:

**Protein:** 20-30%
**Carbs:** 5-10%
**Fats:** 0-3%

The difference is significant: someone eating a higher-protein diet could burn substantially more calories through digestion than someone eating a very low-protein diet. This is supported by research reviewed by Westerterp (2004): replacing 20% of meal calories with protein increased aggregate TEF from 7.1% to 8.3% in one study and from 10.5% to 14.6% in another. In fact, overlooking the thermic effect of food harms the population that most likely relies on those calculations: serious athletes and resistance-trained individuals, who likely eat a higher-protein diet than the average person. While individual TEF values per macronutrient are well established in the literature, the following argument regarding a circular relationship between TEF and caloric/macronutrient breakdown represents a logical synthesis of these findings, rather than a conclusion from any single study. Because TEF accounts for total caloric intake and macronutrient breakdown, optimal caloric intake requires considering TEF. TEF and total caloric intake/macronutrient breakdown have a circular relationship, therefore requiring iterative calculations: recalculating TEF based on the prescribed diet, adjusting gross intake accordingly, and then recalculating TEF until it converges with total caloric intake.

## SECTION 5: INTEGRATING THE FACTORS: THE CASE FOR AN ADAPTIVE METHODOLOGY

Each of the preceding sections has identified a factor that generic calorie calculators ignore and diverge from the current nutrition and exercise science literature — not accounting for lean mass when making BMR estimations (Cunningham, 1980; Frankenfield et al., 2005), not considering training experience when determining ideal rates of weight gain/loss (Smith et al., 2021; Helms et al., 2023; Murphy & Koehler, 2022), ignoring the breakdown of calories into proteins, carbs, and fats (Helms et al., 2014; Morton et al., 2018; Whittaker & Wu, 2021), and failing to properly account for the thermic effect of food (de Jonge & Bray, 1997; Westerterp, 2004). These components are all supported by the exercise science literature, but the integrated methodology presented in this section is my own proposal, not an already validated model. Taken individually, these are all minor adjustments, but together they could vastly change the caloric estimate. However, even a methodology that properly integrates all components remains imperfect due to factors that are extremely difficult to account for accurately, such as the ability to put on muscle and metabolic rate, as the unexplainable variance data from section 2 illustrates—who gained primarily lean vs. fat mass. This study illustrates why, even by accounting for some of these more precise variables discussed in this paper, the calculations could still be far from ideal for some participants. Therefore, the best approach is not only one that accounts for the factors listed in this paper, but one that is adaptive; one that changes reactively based on actual outcomes. Take, for example, someone who should be in a 200-calorie surplus given their training experience and goals, but after a few months they notice they are gaining a significant amount of body fat, even though their surplus should be ideal for maximizing the muscle-to-fat gain ratio. In this case, the trainee should lower their calorie intake. Take another example of a beginner who is eating in a 400-calorie surplus but putting on basically no fat at all after a few months. This trainee could benefit from increasing the surplus, as it may allow them to add even more muscle without additional fat gain. This need for periodic changes to one's plan not only accounts for unpredictable genetic factors but also for metabolic regulation. For example, if someone is in a 500-calorie deficit and losing about 1 pound of fat per week, and after 8 weeks, their fat loss slows dramatically, it may be because their maintenance calories have shifted downward (Martin et al., 2022; Fothergill et al., 2016). In this case, to continue losing weight at the same rate as before, they would need to either increase their EAT/NEAT or reduce their calorie intake. Additionally, if, on paper, someone's maintenance calories should be 2900, but after 2 weeks, they have gained 5 pounds, then adjusting their maintenance calories down significantly would be the logical response. The specific adjustments given in the recalibration examples presented in this section are logically derived but not specifically validated. All things considered, a methodology that accounts for the factors discussed in this paper, along with periodic adjustments based on real-world results, will provide the best accuracy for anyone.

## SECTION 6: A WORKED EXAMPLE

To better understand the proposed methodology presented in this review, let's go through an example calculation for an 82 kg male, who is 14% body fat, moderately active, losing body fat, and resistance training 4 times per week. Figure 1 outlines this six-step process, which the example below walks through in detail.

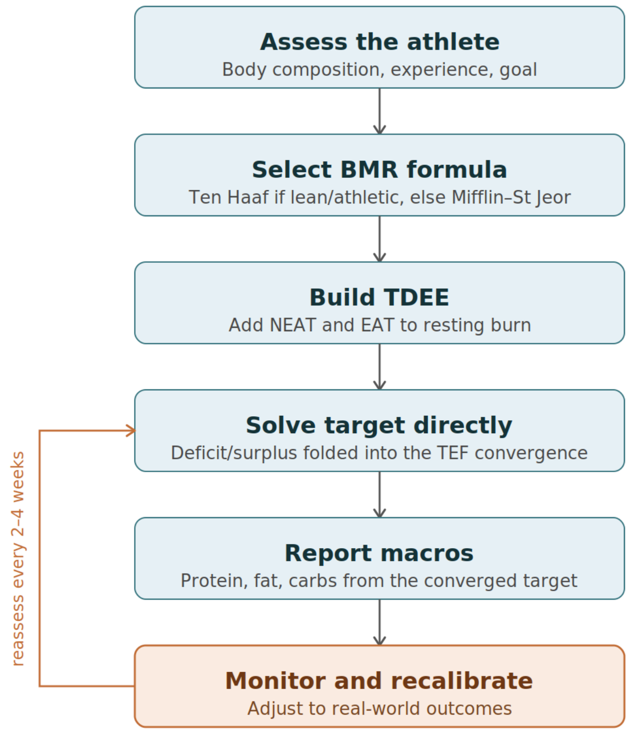


**Figure 1.** *The integrated, adaptive methodology for estimating caloric needs. The calculation sequence (assessment through macro reporting) runs once; the monitor-and-recalibrate step feeds back into the target-solving step on a recurring basis.*

**Step 1:** First, we must determine his BMR, and because he is lean and resistance trained, so we use the Ten Haaf formula for best accuracy (ten Haaf & Weijs, 2014):

Resting kcal = (95.272 × LeanMass(kg) + 2026.161) ÷ 4.184

Plugging in his lean mass (82 kg × 0.86), we get 2090 kcal per day.

(95.272 × 70.5 + 2026.161) ÷ 4.184 = 2090 kcal

**Step 2:** Then, to account for NEAT, we can use a simple BMR multiplier, in this case for moderately active, we can multiply his BMR by 1.35, giving us 2822 kcal.

2090 × 1.35 = 2822 kcal

Next, in order to calculate EAT, we can use a fixed number of calories per weight training session, say 300 in this case for the average workout, giving us an average of 171 kcal per day.

(4 × 300) / 7 = 171 kcal

This brings us to our pre-TEF total of 2993 kcal per day.

2822 + 171

**Step 3:** Immediately, before even accounting for TEF, we can establish the amount of protein, which we can take the average of 2.3-3.1g/kg of lean mass, giving us 2.7g/kg of lean mass, or 190 grams of protein. For fats, we want it to be 20% of the total daily intake, but we do not yet have that intake, so we must wait before calculating. For carbs, we will use the remaining calories after subtracting calories from protein and fat.

**Step 4:** For the calculation of TEF, the following values were chosen as the midpoint of the given ranges in Section 4:

```
Protein: 25%
Carbs: 7.5%
Fats: 1.5%
```

To calculate TEF and therefore maintenance calories, we must use iterative calculations, requiring us to guess a number and adjust accordingly, which in this case converges at 3336 calories, making that this subject's maintenance calories, as seen in this sample calculation:

| Round | Guess | Fat (20%) | Carbs (remainder) | TEF | Next guess |
|---|---|---|---|---|---|
| 1 | 2,993 | 599 | 1,634 | 322 | 3,315 |
| 2 | 3,315 | 663 | 1,892 | 342 | 3,335 |
| 3 | 3,335 | 667 | 1,908 | 343 | 3,336 |

**Step 5:** Then, we subtract the amount of calories we want for the deficit, which in this case, we'll use a standard deficit of 500 kcal. However, simply subtracting 500 calories from 3336 will not yield an accurate number due to the change in macronutrient composition, and therefore the change in TEF. Accordingly, we must apply the same principle applied in Step 4, when solving for maintenance calories, following this form: guess → macros at that guess → TEF → new guess = base + TEF − 500 → repeat.

**Step 6:** This time, the caloric value converges to 2803 calories, less than 2836, the value if you simply subtracted 500 calories. This value leaves us with the following macros: 190g protein, 62g fat, and 371g carbs (the ratio between fat and carbs can be less specific). In fact, with ideal macros here the thermic effect of food works out to be 11.05% of calories burned, rather than the typical blanket estimate of 10%.

This walkthrough purely demonstrates how the calculations would work on a hypothetical individual, not a pre-existing trial. Lastly, it is important to recalibrate calories periodically based on real-world results to better account for any errors, genetic inconsistencies, or metabolic adaptation.

## SECTION 7: LIMITATIONS

The most significant limitation of the integrated methodology proposed in this paper is the same problem that prompted the adoption of an adaptive approach: individual variation. As seen in the study finding that even when protein intake, caloric surplus, and training volume were measured and used as predictors, only 18-40% of the outcomes were explainable (Smith et al., 2021), this shows that no formula, even ones taking into account the variables mentioned in this paper, would provide a one-size-fits-all calculation. The goal of the integrated methodology presented here is not to be 100% accurate, but to be closer than what is currently available from more widely used resources. It is worth noting, though, that a formula that is accurate for 70% of resistance-trained individuals is substantially better than one accurate for only 50%, even if neither is perfect for every individual (O'Neill et al., 2023; Frankenfield et al., 2005).

Several specific limitations in the cited literature deserve to be acknowledged. The Smith et al. (2021) study included only 28 participants, making the sample too small to generalize the findings to the entire population. Additionally, the meta-analysis on BMR prediction equations in athletes included 29 studies with 1,430 participants, which, although somewhat sizeable, is still not representative of the entire athletic population (O'Neill et al., 2023). Furthermore, the experience-based rates of muscle gain commonly attributed to McDonald and Aragon represent practitioner frameworks aggregated from observational data rather than controlled trials, and should be used accordingly (McDonald, n.d.). However, the convergence across multiple independent lines of evidence — BMR formula accuracy, TEF research, deficit thresholds, and protein requirements — all pointing toward individualization despite coming from different research groups using different methodologies, strengthens the overall argument beyond what any single study could establish.

For the integrated methodology presented in this review to work for the general public, substantially more data is required, such as a reliable body fat estimate for lean-mass-based BMR calculation (Cunningham, 1980; Katch & McArdle, 1973), accurate training experience classification, identification of current training phase/goals, and precise macronutrient tracking to accurately calculate iterative TEF (Westerterp, 2004; Westerterp-Plantenga et al., 2009). These more precise calculations are far less widely available than the data current tools rely on, such as height, weight, age, sex, and activity level. That said, body fat percentage measurements are increasingly accessible through consumer devices, such as scales and calipers and/or DEXA scans, though it is important to note that these tests have a real margin for error, which can impede the accuracy of a lean-mass-based BMR calculation. Furthermore, training experience calculations are relatively straightforward for most individuals, and precise macronutrient tracking is already standard practice for many in the fitness space, which is most likely to be affected by inaccuracies of general tools.

Additionally, although not touched on much in this review, there is the margin for error in estimating NEAT and EAT, often poorly estimated by wearable devices.

Lastly, it is worth acknowledging the challenge of adhering to the methodology presented in this paper. Frequent recalibration, accurate and consistent weigh-ins, and precise calorie/macronutrient tracking can be demanding and have room for error, partially capping the practical benefit.

## CONCLUSION

Generic fitness calculators fail to account for four specific dimensions that the literature consistently supports—lean-mass-based BMR formula selection, experience-based caloric surpluses/deficits, evidence-based macronutrient breakdown, and iterative TEF calculations. Taken together, ignoring these factors compounds to produce large systemic errors that are largest for the population most likely to use these tools: resistance-trained athletes following high-protein diets. However, even a fully integrated methodology remains insufficient, as it fails to account for individual genetic variation and metabolic regulation, making an adaptive approach—constant recalculation based on real-world outcomes—essential for optimal results. Further research—longitudinal studies comparing body composition changes between users following a conceptual and adaptive integrated methodology, such as the approach presented in this review, and generic calculators—is required to conclusively validate it. Nevertheless, the development of accessible tools that implement lean-mass-based BMR calculations, experience-level calorie and macronutrient targets, iterative TEF accounting, and structured, periodic outcome-based recalibration would represent a meaningful leap in the field of applied sports nutrition.

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Emmett Goldberg is a high school student with a passion for math, science, and nutrition. His interest in the topics discussed in this review stems from his own experiences navigating incomplete information in the fitness industry. He is the creator of PhysioPlan (https://physioplan.org/), a tool that implements the individualized and adaptive methodology presented in this review into an algorithm to help simplify the nuances of the fitness journey for the general public. Currently, he is working with about 30 individuals and actively tracking their progress through PhysioPlan.