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REVIEW

Modeling in clinical nutrition: does it add to patient care?

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BACKGROUND/OBJECTIVES: Remarkable improvements in mathematical methodology combined with knowledge and data on the response of the human body to changes in nutrition, activity and environment have led to a rapid expansion of mathematical models that predict, describe and aggregate conclusions in nutrition. Although mathematical models in nutrition have made significant advances in predictive accuracy and physiological descriptions, these advances have compromised model simplicity, introducing obstacles to their widespread application and contribution to clinical care. The challenge of model complexity is moderated by delivery through well-designed software.
SUBJECTS/METHODS: We reviewed several recent and novel web-based mathematical models related to nutrition and describe the successful application of a dynamic mathematical model to patient care implemented through counseling software in a recent weight-loss intervention. To illustrate the power of model transfer through software, we designed a Visual Basic macro within Microsoft Excel to deliver predictions from six well-established and validated resting energy expenditure formulas in children and adults.
RESULTS: The six resting energy expenditure models that were deployed using the Visual Basic Application developer ranged in technical complexity requiring decision trees, calculation of nonlinear terms or inclusion of multiple covariates. The developed software allows users to select specific models and desired units. After input of individual height, weight, age and sex data through a user form, individuals can effortlessly view predictions.
CONCLUSIONS: Advances in web-based and widely accessible software provide the capacity to deliver more accurate and physiologically realistic nutrition-related models, and ultimately translating model results to patient care.

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Keywords: mathematical modeling; resting metabolic rate; weight change

INTRODUCTION

Models in nutrition have historically relied on a balance between accuracy and mathematical tractability to facilitate application to patient care. These long-standing models are so deeply ingrained in nutrition that they are rarely considered as actual models. For example, the familiar body mass index, represents a model of adiposity derived from geometric assumptions involving the human body.[1] Likewise, the 3500-kcal weight-loss rule,[2] which states that a 3500-kcal deficit resulting from caloric restriction or increased activity results in 1 lb of weight loss, is frequently applied to estimate expected weight loss in patients undergoing life-style interventions.[3]

The emergence of new mathematical methods such as dynamic modeling, data mining, neural networks and machine learning along with worldwide efforts to integrate scientific disciplines has led to incredible advances in modeling on numerous nutritional fronts. Some novel modeling examples are reflected in the prediction of individual energy expenditure from portable sensor devices,[4–6] weight change arising from changes in diet and activity,[7,8] and costs associated with the obesity epidemic.[9,10]

Despite the advances and the incredibly creative merging between the mathematical sciences and nutrition, model improvements to predictive accuracy and quality of physiological description also generated more complex and less tractable mathematical formulae that often require discipline-specific and trained mathematical experts to deliver model predictions.[11] Thus, increased model complexity limits widespread application of models to patient care.

Here, we describe several examples that have moved beyond this limitation by housing advanced models within web-based or widely accessible software. We describe the successful application of one of these models delivered through counseling software to directly improve patient care and develop a new software tool to predict resting metabolic rates.

Web-based calculators

Web-based Java programs offer a delivery platform for models that were traditionally only accessible through specialized mathematical software. Although programming stand-alone Java software to simulate complex mathematical models is a computationally demanding task requiring new and in some cases novel methods specially tailored to each model, the end reward for public health is high. The developed model is now accessible to clinicians and patients and can be applied to deliver novel treatment strategies and estimate expected patient response.

Recently, two dynamic models that predict weight change from changes in energy balance were developed into Java programs; http://bwsimulator.niddk.nih.gov/[7] and http://pbrc.edu/research-and-faculty/calculators/weight-loss-predictor/.[12] The second program was developed into stand-alone counseling software and successfully applied by clinicians to guide patient weight

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loss in a recent intervention.[13] An additional calculator accessible at http://pbrc.edu/research-and-faculty/calculators/gestational-weight-gain/ was developed for a dynamic model predicting pregnancy weight gain in response to changes in maternal intake,[14] which is currently being clinically applied to facilitate weight gain management during pregnancy in a cohort of overweight and obese women (http://clinicaltrials.gov/ct2/show/NCT01610752).

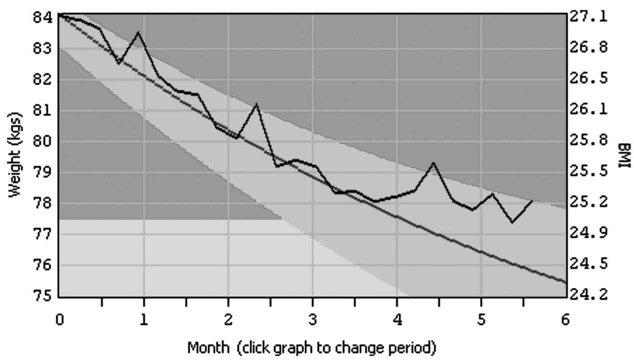

Figure 1. Example of an individual weight graph[12] (smooth curve) generated using the counseling software[13] in a recent weight-loss intervention. The non-smooth black curve represents actual patient weight that fell within the shaded zone surrounding the weight loss curve indicating patient adherence.

Mathematical models applied to patient care: a recent example

A recent weight-loss experiment[13] conducted at the Pennington Biomedical Research Center studied the effects of 20 obese patients undergoing weight loss through caloric restriction with expected weight loss guided by a validated dynamic mathematical model that predicted weight change.[12,15] The dynamic mathematical model was used to generate a personalized graph for each participant depicting a range or 'zone' of body weights over time that would be achieved if adherent to the diet (Figure 1). Ongoing weekly body weights were depicted on the same graph that was then applied to guide treatment recommendations (participants were considered adherent to the diet if their weight was in this zone). The model, zones and individual weight graph were housed within an interactive counseling software program developed using the Java programming language and executed by the interventionists without requiring external involvement of a mathematical expert (Figure 1).

Resting metabolic rate clinical tool

We programmed six established and validated resting metabolic rate prediction formulas using the Visual Basic Application developer within Microsoft Excel. Four of the six resting metabolic rate formulas were developed for an adult population ($\geqslant$18 years); the Livingston–Kohlstadt model,[16] Harris–Benedict model,[17] the Mifflin–St Jeor model[18] and the Schofield model[19] applied by the World Health Organization. We additionally included two models specific to children aged 5–18 years: the Schofield model for

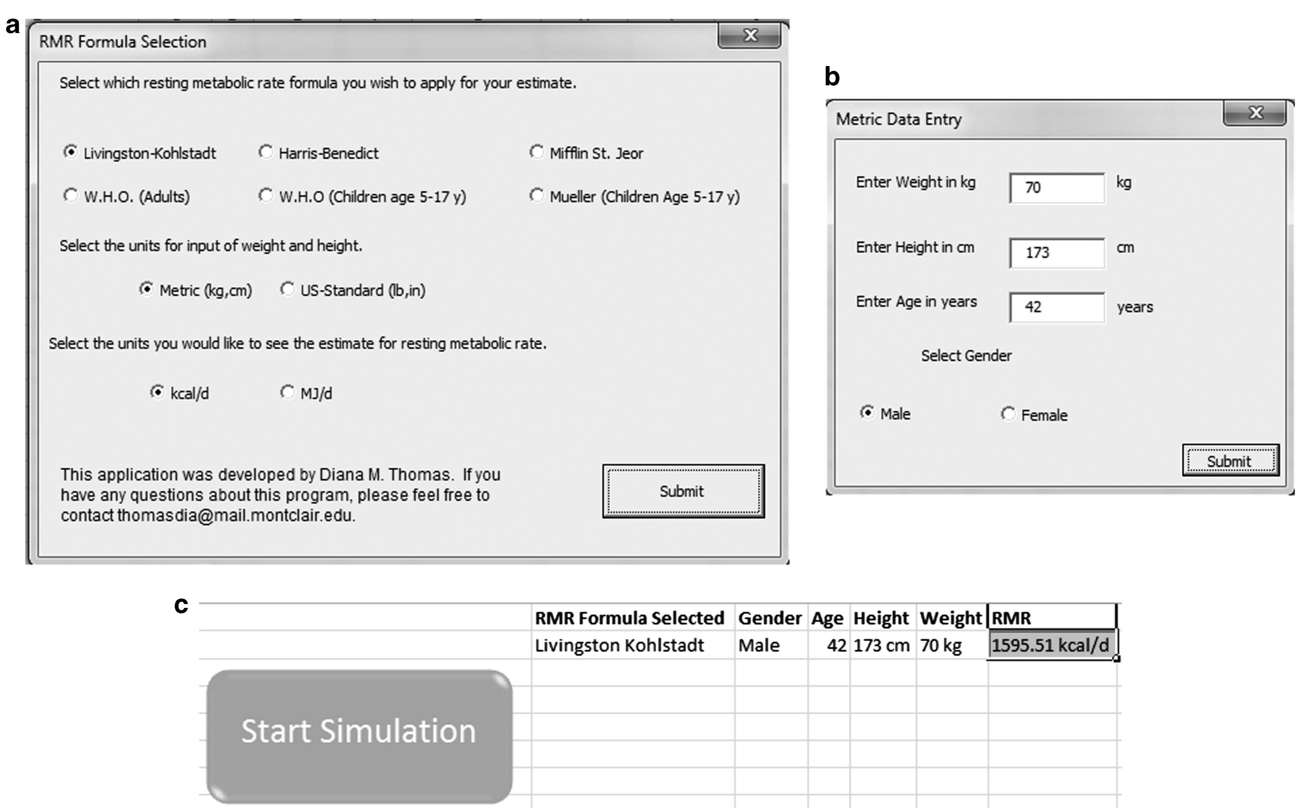

Figure 2. Screen shot of software developed to predict resting metabolic rate from user-selected choice of six different established resting metabolic rate equations.[16–19,21] (**a**) Depicts the interface where user selects choice of model, input units and output units. (**b**) Depicts individual age, height, sex and weight entry form and (**c**) demonstrates sample output. The calculator is available as a downloadable excel file at http://www.montclair.edu/csam/center-quantitative-obesity/links/. Users should select the prompt to enable macros to access the interactive program.

children[19] and the more recently developed Müller model.[20] The newly developed clinical tool (Figure 2) can be accessed at http://www.montclair.edu/csam/center-quantitative-obesity/links/ under Health Calculators.

DISCUSSION

Over the past few decades, rapid advances in mathematical modeling have vastly improved predictions and physiological descriptions in nutrition research. The advances in modeling have also increased the complexity of the models, challenging the capacity for direct clinical applications.

We have been able to override this limitation by successfully deploying our dynamic model in a recent weight-loss intervention through a clinical counseling software tool.[13] We demonstrate the power of this method by developing a similar tool to deliver predictions from six well-established and validated resting metabolic rate formulas.

Translation of mathematical models to improve patient care requires a highly interdisciplinary effort to generate the best possible models from state of the art data that sufficiently capture and explain physiological reality and provide improved predictive accuracy. Communication between model developers, professional programmers and clinicians is essential for designing accessible and viable software that delivers these model results to a patient's bedside.

CONFLICT OF INTEREST

Diana Thomas is a consultant for Jenny Craig.

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