Report

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Energy compensation and adiposity in humans

Highlights

- Energy compensation in humans was analyzed from daily and basal energy expenditure
- Reduced BEE results in energy compensation of 28%
- Degree of energy compensation varied between people of different body composition

Authors

Vincent Careau, Lewis G. Halsey, Herman Pontzer, ..., William W. Wong, Yosuke Yamada, John R. Speakman

Correspondence

vcareau@uottawa.ca (V.C.), l.halsey@roehampton.ac.uk (L.G.H.), herman.pontzer@duke.edu (H.P.), aluke@luc.edu (A.H.L.), jennifer.rood@pbrc.edu (J.R.), sagayama.hiroyuki.ka@u.tsukuba.ac.jp (H.S.), dschoell@nutrisci.wisc.edu (D.A.S.), wwong@bcm.edu (W.W.W.), yyamada831@gmail.com (Y.Y.), j.speakman@abdn.ac.uk (J.R.S.)

In brief

Energy compensation is the concept that not all the energy spent when activity levels increase translates to additional energy spent that day, but it is poorly characterized. Careau, Halsey et al. find that in humans, energy compensation averages 28%, i.e., only 72% of the extra calories we spend on additional activity translates into extra calories burned that day.

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Report

Energy compensation and adiposity in humans

Vincent Careau,[1,69,*] Lewis G. Halsey,[2,68,69,71,*] Herman Pontzer,[3,4,*] Philip N. Ainslie,[5] Lene F. Andersen,[6] Liam J. Anderson,[7] Lenore Arab,[8] Issad Baddou,[9] Kweku Bedu-Addo,[10] Ellen E. Blaak,[11] Stephane Blanc,[12,13] Alberto G. Bonomi,[14] Carlijn V.C. Bouten,[15] Maciej S. Buchowski,[16] Nancy F. Butte,[17] Stefan G.J.A. Camps,[11] Graeme L. Close,[5] Jamie A. Cooper,[12] Sai Krupa Das,[18] Richard Cooper,[19] Lara R. Dugas,[19,20] Simon D. Eaton,[21] Ulf Ekelund,[22] Sonja Entringer,[23,24] Terrence Forrester,[25] Barry W. Fudge,[26] Annelies H. Goris,[11] Michael Gurven,[27]

(Author list continued on next page)

[1]Department of Biology, University of Ottawa, Ottawa, ON, Canada
[2]School of Life and Health Sciences, University of Roehampton, London, UK
[3]Evolutionary Anthropology, Duke University, Durham, NC, USA
[4]Duke Global Health Institute, Duke University, Durham, NC, USA
[5]Research Institute for Sport and Exercise Sciences, Liverpool John Moores University, Liverpool, UK
[6]Department of Nutrition, Institute of Basic Medical Sciences, University of Oslo, 0317 Oslo, Norway
[7]University of Birmingham, Birmingham, UK
[8]David Geffen School of Medicine, University of California, Los Angeles, Los Angeles, CA, USA
[9]Unité Mixte de Recherche en Nutrition et Alimentation, CNESTEN, Université Ibn Tofail URAC39, Regional Designated Center of Nutrition Associated with AFRA/IAEA, Kénitra, Morocco
[10]Department of Physiology, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[11]Maastricht University, Maastricht, the Netherlands
[12]Nutritional Sciences, University of Georgia, Athens, GA, USA
[13]Institut Pluridisciplinaire Hubert Curien, CNRS Université de Strasbourg, Strasbourg UMR7178, France
[14]Phillips Research, Eindhoven, the Netherlands
[15]Department of Biomedical Engineering and Institute for Complex Molecular Systems, Eindhoven University of Technology, Eindhoven, the Netherlands
[16]Division of Gastroenterology, Hepatology and Nutrition, Department of Medicine, Vanderbilt University, Nashville, TN, USA
[17]Department of Pediatrics, Baylor College of Medicine, USDA/ARS Children's Nutrition Research Center, Houston, TX, USA
[18]Jean Mayer USDA Human Nutrition Research Center on Aging, Tufts University, 711 Washington Street, Boston, MA 02111, USA
[19]Department of Public Health Sciences, Parkinson School of Health Sciences and Public Health, Loyola University, Maywood, IL, USA

(Affiliations continued on next page)

SUMMARY

Understanding the impacts of activity on energy balance is crucial. Increasing levels of activity may bring diminishing returns in energy expenditure because of compensatory responses in non-activity energy expenditures.[1–3] This suggestion has profound implications for both the evolution of metabolism and human health. It implies that a long-term increase in activity does not directly translate into an increase in total energy expenditure (TEE) because other components of TEE may decrease in response—energy compensation. We used the largest dataset compiled on adult TEE and basal energy expenditure (BEE) (n = 1,754) of people living normal lives to find that energy compensation by a typical human averages 28% due to reduced BEE; this suggests that only 72% of the extra calories we burn from additional activity translates into extra calories burned that day. Moreover, the degree of energy compensation varied considerably between people of different body compositions. This association between compensation and adiposity could be due to among-individual differences in compensation: people who compensate more may be more likely to accumulate body fat. Alternatively, the process might occur within individuals: as we get fatter, our body might compensate more strongly for the calories burned during activity, making losing fat progressively more difficult. Determining the causality of the relationship between energy compensation and adiposity will be key to improving public health strategies regarding obesity.

RESULTS AND DISCUSSION

The contexts within which energy compensation occur, the extent to which it occurs,[4] and the processes involved are far from resolved.[2,5–7] Using the largest dataset on human energy expenditure ever assembled, by estimating the relationships between total, activity, and basal energy expenditure (TEE, AEE, and BEE), we test the mutually exclusive predictions from the

Catherine Hambly,[29] Asmaa El Hamdouchi,[9] Marije B. Hoos,[11] Sumei Hu,[30] Noorjehan Joonas,[31] Annemiek M. Joosen,[11] Peter Katzmarzyk,[32] Kitty P. Kempen,[11] Misaka Kimura,[33] William E. Kraus,[34] Robert F. Kushner,[35] Estelle V. Lambert,[36] William R. Leonard,[37] Nader Lessan,[38] Corby K. Martin,[32] Anine C. Medin,[6,39] Erwin P. Meijer,[11] James C. Morehen,[5,40] James P. Morton,[5] Marian L. Neuhouser,[41] Theresa A. Nicklas,[17] Robert M. Ojiambo,[42,43] Kirsi H. Pietiläinen,[44] Yannis P. Pitsiladis,[45] Jacob Plange-Rhule,[46,70] Guy Plasqui,[47] Ross L. Prentice,[41] Roberto A. Rabinovich,[48] Susan B. Racette,[49] David A. Raichlen,[50] Eric Ravussin,[31] John J. Reilly,[51] Rebecca M. Reynolds,[52] Susan B. Roberts,[18] Albertine J. Schuit,[53] Anders M. Sjödin,[54] Eric Stice,[55] Samuel S. Urlacher,[56] Giulio Valenti,[11] Ludo M. Van Etten,[11] Edgar A. Van Mil,[57] Jonathan C.K. Wells,[58] George Wilson,[5] Brian M. Wood,[59,60] Jack Yanovski,[61] Tsukasa Yoshida,[66]

(Author list continued on next page)

[20]Division of Epidemiology and Biostatistics, School of Public Health and Family Medicine, University of Cape Town, Cape Town, South Africa
[21]Developmental Biology & Cancer Department, University College London, London, UK
[22]Department of Sport Medicine, Norwegian School of Sport Sciences, Oslo, Norway
[23]Charité – Universitätsmedizin Berlin, corporate member of Freie Universität Berlin, Humboldt-Universität zu Berlin, and Berlin Institute of Health (BIH), Institute of Medical Psychology, Berlin, Germany
[24]University of California, Irvine, Irvine, CA, USA
[25]Solutions for Developing Countries, University of the West Indies, Mona, Kingston, Jamaica
[26]University of Glasgow, Glasgow, UK
[27]Department of Anthropology, University of California, Santa Barbara, Santa Barbara, CA, USA
[28]Center for Energy Metabolism and Reproduction, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China
[29]Institute of Biological and Environmental Sciences, University of Aberdeen, Aberdeen, UK
[30]State Key Laboratory of Molecular Developmental Biology, Institute of Genetics and Developmental Biology, Chinese Academy of Sciences, Beijing, China
[31]Central Health Laboratory, Ministry of Health and Wellness, Port Louis, Mauritius
[32]Pennington Biomedical Research Center, Baton Rouge, LA, USA
[33]National Institute of Health and Nutrition, National Institutes of Biomedical Innovation, Health and Nutrition, Tokyo, Japan
[34]Department of Medicine, Duke University, Durham, NC, USA
[35]Northwestern University, Chicago, IL, USA
[36]Health through Physical Activity, Lifestyle and Sport Research Centre (HPALS), FIMS International Collaborating Centre of Sports Medicine, Department of Human Biology, Faculty of Health Sciences, University of Cape Town, Cape Town, South Africa
[37]Department of Anthropology, Northwestern University, Evanston, IL, USA
[38]Imperial College London Diabetes Centre, Abu Dhabi, UAE, Imperial College London, London, UK
[39]Department of Nutrition and Public Health, Faculty of Health and Sport Sciences, University of Agder, 4630 Kristiansand, Norway
[40]The FA Group, Burton-Upon-Trent, Staffordshire, UK
[41]Division of Public Health Sciences, Fred Hutchinson Cancer Research Center and School of Public Health, University of Washington, Seattle, WA, USA
[42]Moi University, Eldoret, Kenya
[43]University of Global Health Equity, Kigali, Rwanda
[44]Obesity Research Unit, Research Program for Clinical and Molecular Metabolism, Faculty of Medicine, University of Helsinki and Obesity Center, Abdominal Center, Helsinki University Hospital and University of Helsinki, Helsinki, Finland
[45]University of Brighton, Eastbourne, UK
[46]Department of Physiology, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[47]Department of Nutrition and Movement Sciences, Maastricht University, Maastricht, the Netherlands
[48]University of Edinburgh, Edinburgh, UK
[49]Program in Physical Therapy and Department of Medicine, Washington University School of Medicine, St. Louis, MO, USA
[50]Biological Sciences and Anthropology, University of Southern California, Los Angeles, CA, USA
[51]University of Strathclyde, Glasgow, Scotland, UK
[52]Centre for Cardiovascular Science, Queen's Medical Research Institute, University of Edinburgh, Edinburgh, UK
[53]University of Tilburg, Tilburg, the Netherlands
[54]Department of Nutrition, Exercise and Sports, Copenhagen University, Copenhagen, Denmark
[55]Stanford University, Stanford, CA, USA
[56]Department of Anthropology, Baylor University, Waco, TX, USA
[57]Maastricht University, Maastricht and Lifestyle Medicine Center for Children, Jeroen Bosch Hospital's-Hertogenbosch, Maastricht, the Netherlands
[58]Population, Policy and Practice Research and Teaching Department, UCL Great Ormond Street Institute of Child Health, London, UK
[59]University of California, Los Angeles, Los Angeles, USA
[60]Max Planck Institute for Evolutionary Anthropology, Department of Human Behavior, Ecology, and Culture, Leipzig, Germany
[61]Growth and Obesity, Division of Intramural Research, NIH, Bethesda, MD, USA
[62]Faculty of Health and Sport Sciences, University of Tsukuba, Ibaraki, Japan

(Affiliations continued on next page)

Xueying Zhang,[29,30] Alexia J. Murphy-Alford,[63] Cornelia U. Loechl,[63] Amy H. Luke,[64,*] Jennifer Rood,[32,*] Hiroyuki Sagayama,[62,*] Dale A. Schoeller,[65,*] William W. Wong,[17,*] Yosuke Yamada,[33,66,*] and John R. Speakman,[28,29,30,67,*] the IAEA DLW database group

[63]Nutritional and Health Related Environmental Studies Section, Division of Human Health, International Atomic Energy Agency, Vienna, Austria
[64]Department of Public Health Sciences, Loyola University Chicago, Maywood, IL, USA
[65]Biotech Center and Nutritional Sciences, University of Wisconsin, Madison, WI, USA
[66]Institute for Active Health, Kyoto University of Advanced Science, Kyoto, Japan
[67]Shenzhen Key Laboratory of Metabolic Health, CAS Center of Excellence in Animal Evolution and Genetics, Kunming, China
[68]Twitter: @lewis_halsey
[69]These authors contributed equally
[70]Deceased
[71]Lead contact
*Correspondence: vcareau@uottawa.ca (V.C.), l.halsey@roehampton.ac.uk (L.G.H.), herman.pontzer@duke.edu (H.P.), aluke@luc.edu (A.H. L.), jennifer.rood@pbrc.edu (J.R.), sagayama.hiroyuki.ka@u.tsukuba.ac.jp (H.S.), dschoell@nutrisci.wisc.edu (D.A.S.), wwong@bcm.edu (W. W.W.), yyamada831@gmail.com (Y.Y.), j.speakman@abdn.ac.uk (J.R.S.)
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three energy expenditure models (Figure 1) for individuals with unremarkable lifestyles generating natural variation in TEE over time, and without food restriction. Determining which of these energy expenditure models apply to humans under typical, free-living conditions, and quantifying its effects, will progress our understanding of the evolution and control of metabolism, and may provide key physiological information for management strategies for weight control.

We extracted paired measurements of BEE (respirometry) and TEE (doubly labeled water [DLW][19]) for 1,754 adults from the International Atomic Energy Agency DLW database v.3.1.2.[20] All estimates of TEE were made using a standard calculation across all studies.[21] Controlling for age (years), sex, and body composition (i.e., fat-free mass [FFM] in kg, derived from the body water dilution spaces, and fat mass [FM] in kg, calculated as the difference between body mass and fat-free mass), a multiple regression of TEE as a function of BEE revealed an overall positive and highly significant relationship between TEE and BEE, with a slope of $b \pm SE = 0.723 \pm 0.049$ (Table S1A) and 95% confidence intervals (CIs) that exclude both 0 and 1 (CI: 0.626; 0.820). The positive relationship between BEE and TEE is not surprising, given that BEE represents the largest component of TEE (Figure 1B). Due to the part-whole relationship, however, the slope between BEE and TEE should be 1 unless the active and basal components of energy expenditure are positively or negatively linked (as postulated in the performance and compensation models, respectively; Figure 1C). Because our analysis revealed that the slope is significantly <1 (Figure 2A), this indicates that a considerable degree (27.7%) of compensation occurred between the active and basal components of energy expenditure.

To further illustrate compensation, we calculated the AEE for each individual by subtracting BEE from 0.9*TEE (TEE adjusted to account for the thermic effect of food). A multiple regression of AEE as a function of BEE (with age, sex, and body composition as covariates) revealed an overall negative and highly significant relationship, with a slope of $b \pm SE = -0.349 \pm 0.044$ ($t = 7.86$, $p < 0.0001$; Table S1A; Figure 2B) and 95% CI that excludes 0 (CI: −0.436; −0.262). These findings concur with those from the model regressing TEE as a function of BEE. Note that, in principle, one mechanism that does not represent energy compensation and yet could, in principle, create the observed patterns is that people who are more active (and have a higher AEE) have a greater proportion of muscle mass,[22] which increases FFM without substantively increasing BEE,[23] resulting in more active people having a low mass-corrected BEE. However, this possibility can be disregarded given that our analysis indicates energy compensation in people having accounted for variation in their FFM by its inclusion as a covariate (as both a main effect and as an interaction term with BEE and age).

Thus, humans living typical modern lives—not undertaking exceptional levels of activity or experiencing chronic food shortages—exhibit a fairly strong compensation between the energy they expend on activity and that expended on basal metabolic processes; over the long term, more than a quarter of the extra calories burned by people during activity do not translate into extra calories expended that day. Presumably, such compensation would have been adaptive for our ancestors because it minimized food energy demands and hence reduced the time needed for foraging, the advantages of which may include reducing exposure to predation. However, it is potentially maladaptive for modern-living humans exercising to try to burn off excess food consumption, given the chain of association linking high-density foods to greater energy intake,[24] obesity,[25] and its related diseases.[26]

Public health initiatives often include prescribed increases in activity in part to increase TEE and thereby control weight gain or promote fat loss.[27] Such a prescription, however, often assumes that costs of activity are additively related to basal costs,[28] which our analyses suggest is untrue. It will therefore be important when prescribing personalized exercise plans for controlling or reducing weight, and managing patient expectations, to know if the degree of long-term energy compensation changes with age and other demographic variables such as sex. It is well known that older individuals are more at risk of obesity than are younger individuals. To test if older people, and potentially one sex more than the other, exhibit greater energy compensation, we took advantage of the information on sex, age, and body composition (measured by isotope dilution) included in our dataset, which consisted of 692 men and 1,062 women aged 18 to 96 years, with FFM ranging from 24.3 to 97.1 (median: 47.64 kg) and body mass index (BMI) ranging from 12.5 to 61.7 (median: 25.2 kg/m^2). To test if the slope

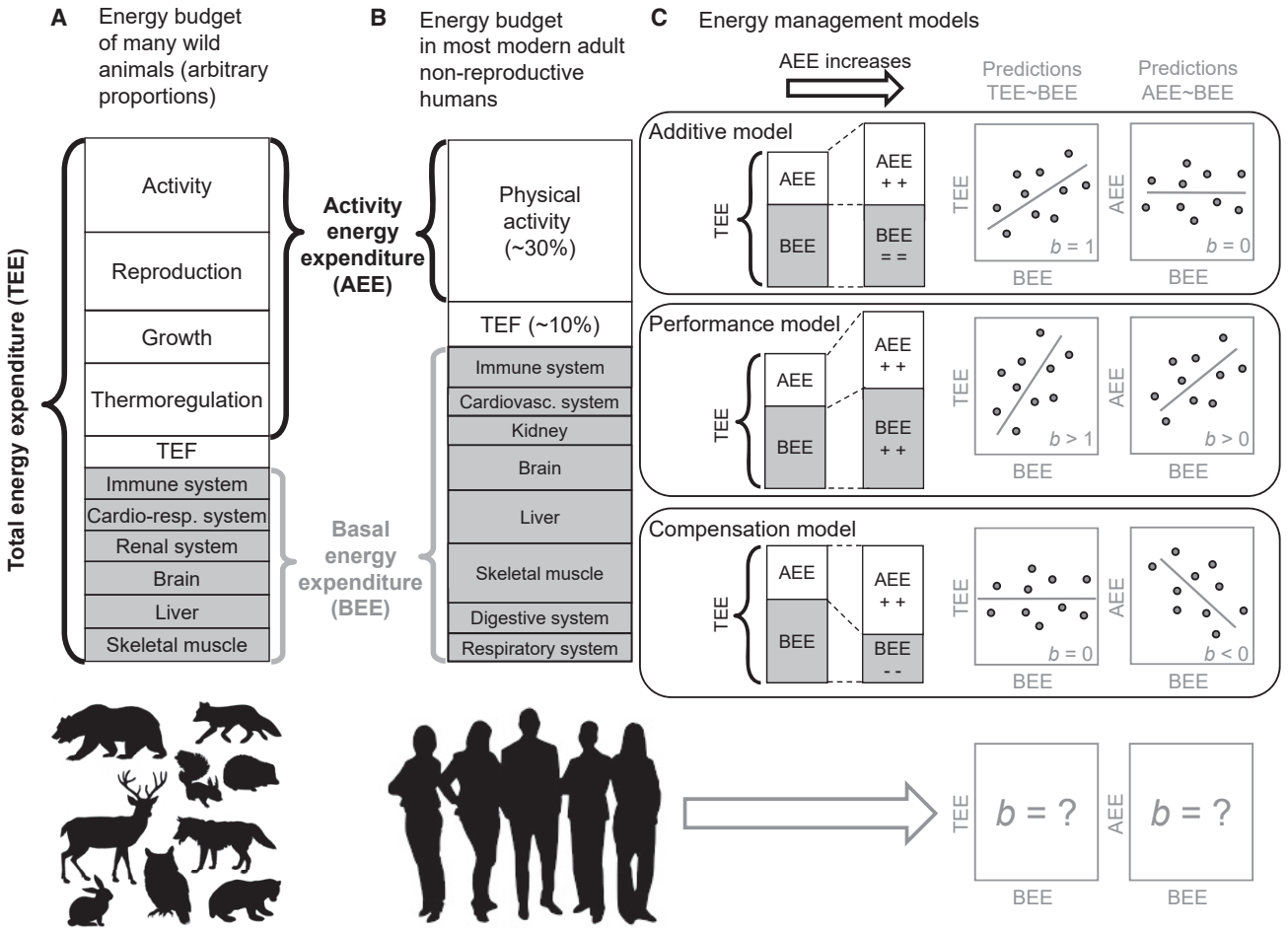

Figure 1. Energy budgets and competing hypotheses

(A) Representation of the total energy expenditure (TEE) of endothermic animals as the sum of the energy invested in activity, reproduction, growth, thermoregulation, digestion (thermic effect of food; TEF), and basal energy expenditure (BEE; the minimum amount of energy required for the functioning [e.g., breathing] and the maintenance [e.g., tissue turnover] of vital systems). Proportions are somewhat arbitrary but recognize that in vertebrates BEE is typically a minor element of TEE.[8] Any source of energy expenditure above BEE (except TEF) is apportioned as activity energy expenditure (AEE), which includes the costs of thermoregulation, reproduction, and growth when present.

(B) Representation of the TEE of most non-reproductive adult humans, in which there are no energy costs of growth or reproduction, and the cost of thermoregulation is assumed to be negligible. In this simplified energy budget, the proportions recognize that in adult humans ~60% of energy is spent on BEE (categorized into proportions based loosely on Müller et al.[9]), and most of the AEE component is indeed represented by physical activity, including locomotion, posture, and "fidgeting."[10]

(C) Illustration of the various models that have been proposed to describe how humans and other animals manage their energy budget,[11–15] and their associated predictions about the slope (*b*) of the relationship between TEE and BEE and between AEE and BEE. The left stack bar shows a simplified baseline version of TEE as the sum of BEE and AEE. Comparing the left versus right stacks shows the mean effect of an increase in AEE on BEE and TEE. The regression lines in the panels to the right show the predicted relationships between TEE and BEE and between AEE and BEE; example individual data points have been included to illustrate the predicted relationship in addition to some unexplained variation. The additive model assumes that AEE and BEE are independent and thus uncorrelated. Therefore, variation in BEE should add up to variation in TEE, with $b = 1$ due to part-whole correlation. In other words, the additive model predicts that additional calories burned by undertaking extra activity results in an equivalent increase in TEE. By contrast, the performance model assumes that a greater "metabolic machinery" is needed to support higher AEE due to increased assimilation of energy, and thus $b > 1$ for the relationship between TEE and BEE. That is, the performance model predicts that the resultant total calories burned due to activity will be higher than just the calories expended during the activity because of additional energy spent on subsequent physical recovery and maintenance of a more expensive metabolic machinery to support this behavior. Alternatively, both humans and animals may respond to greater energy being expended on activity over the long term by reducing the energy expended on other processes, a phenomenon captured by the compensation model. The compensation model assumes that energy budgets are somewhat constrained, which forces trade-offs between energy invested into AEE and BEE, thus predicting a negative relationship between AEE and BEE and therefore $b < 1$ for the relationship between TEE and BEE. It is currently unknown whether energy compensation in humans occurs only under extreme conditions, or at least only during periods of prescribed exercise, where measured or inferred energy compensation has been documented on several occasions,[16–18] or instead whether it is the default model of energy expenditure in humans living typical lives, where activity and energy intake are naturally adjusted over time.

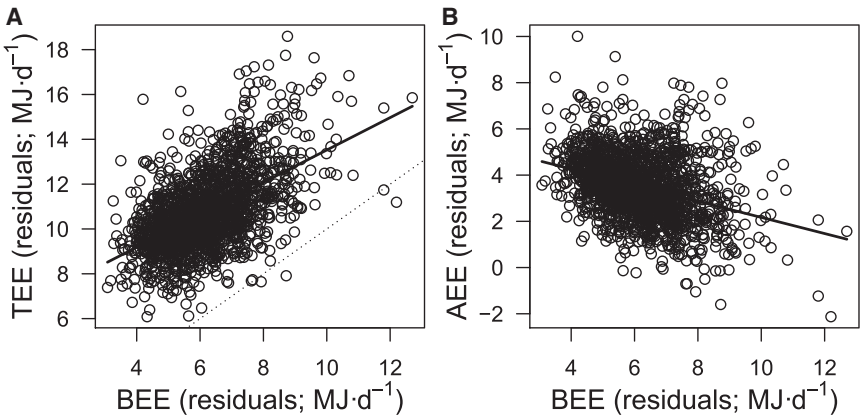

Figure 2. Energy compensation in humans

(A) Total energy expenditure (TEE; MJ·d^{-1}) and (B) activity energy expenditure (AEE; MJ·d^{-1}) as a function of basal energy expenditure (BEE; MJ·d^{-1}) in 1,754 subjects included in this study, controlling for sex, age, and body composition. (A) illustrates how the slope of the TEE-BEE relationship is <1 (compared to the 1:1 dotted line), whereas (B) illustrates the negative relationship between AEE and BEE.

(*b*) of the TEE-BEE and AEE-BEE relationships changes according to sex, age, and body composition, we added the interaction terms between BEE and each of these factors to the multiple regression model (in addition to other two-way interactions between sex, age, and body composition that control for sex differences and age-related changes in body composition; Table S1B). Overall, energy compensation was not different in men versus women and did not vary with age (i.e., BEE × sex and BEE × age interactions; Table S1B). Hence, energy compensation seems to be a general phenomenon that applies equally to men and women, young and old. Note that FFM and FM were derived from isotope dilution, assuming a constant ratio for FFM hydration (73.2%), but according to published literature, FFM hydration may not be constant with adult age. However, any variation is probably small,[29] and indeed unpublished analyses on data for over 1,000 adults with ages ranging from 20 to over 70 indicate that the ratio of total body weight to FFM hardly changes (S. Heymsfield, personal communication).

Interestingly, the BEE × FM interaction was significant with a negative estimate (Table S1B), indicating that the slope of the TEE-BEE and AEE-BEE relationships decreases as FM increases. In other words, controlling for sex, age, and FFM, compensation increases with FM. People that are at the 10th percentile of the BMI distribution compensate 27.7% of activity calories, whereas people at the 90th percentile compensate 49.2% of activity calories (Figure 3). It appears then that individuals with greater fat levels are predisposed to increased adiposity either because they are stronger energy compensators or because they become stronger compensators as they get fatter. If the former, then two people can be equally active, yet one puts on fat mass while the other stays lean. If the latter, then such a positive feedback loop may imply that using exercise as a strategy to escape high adiposity becomes less and less effective. Resolving the causality of this relationship between fat mass and energy compensation might be key to better deploying exercise in the fight against the growing obesity pandemic.

The energy compensation detected in the aforementioned analysis can be the result of processes occurring at two distinct levels of covariation: between individuals and within individuals. Energy compensation at the between-individual level would indicate that people with higher-than-average AEE tend to have a lower-than-average BEE—a covariance due to genetic and/or permanent environmental factors that would cause the between-individual TEE-BEE slope ($b_{between}$) to be <1. By contrast, energy compensation at the within-individual level would indicate that, for a given individual, reversible increases in AEE are accompanied by decreases in BEE, and vice versa, which would cause the

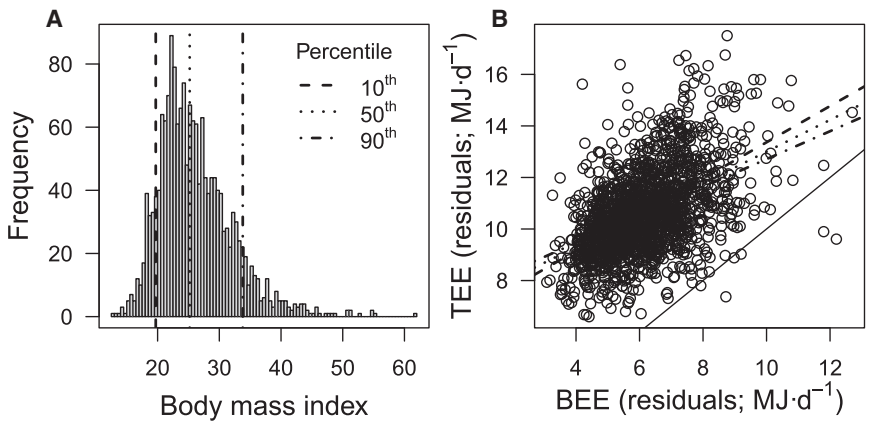

Figure 3. Compensation increases with fat mass

(A) Frequency distribution of body mass index in the 1,754 subjects included in this study, showing where the 10th, 50th, and 90th percentiles lie (long dash, short dash, and dash-dot lines, respectively).

(B) Total energy expenditure (TEE; MJ·d^{-1}) as a function of basal energy expenditure (BEE; MJ·d^{-1}), controlling for sex, age, and body composition. This figure illustrates the significant BEE × FM interaction (Table S1B), showing how compensation increases from 27.7% in people at the 10th percentile of the BMI distribution (long dash line) to 49.2% in people at the 90th percentile of the BMI distribution (dash-dot line). Relationships are plotted separately for three broad BMI categories, but FM is treated as a continuous variable in the analysis (see Table S1B for estimates). The thin solid line indicates a 1:1 relationship.

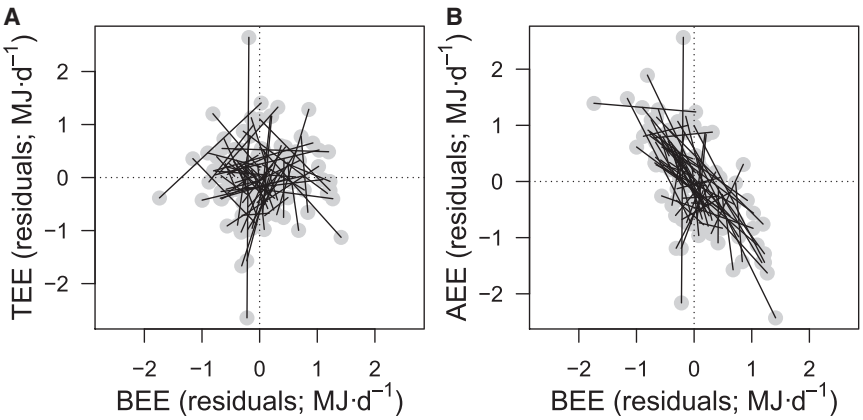

Figure 4. Energy trade-offs within individuals

Residual (A) total energy expenditure (TEE; $MJ \cdot d^{-1}$) and (B) activity energy expenditure (AEE; $MJ \cdot d^{-1}$) as a function of basal energy expenditure (BEE; $MJ \cdot d^{-1}$) in elderly men and women (n = 68) with two pairs of TEE-BEE measures each. Within-individual slopes are illustrated by the thin black lines connecting the two residual values (gray dots; extracted from the bivariate mixed model; Table S2) for each individual.

within-individual TEE-BEE slope (b_{within}) to be <1. To partition the relationship between TEE and BEE at the between- and within-individual levels, we re-analyzed data representing paired measurements of 36 men and 32 women aged between 70 and 90 years sampled 7 years apart within the context of a longitudinal study.[30] This dataset provides the opportunity to estimate the extent of energy compensation occurring both between and within individuals in elderly people. Using a bivariate mixed model, we partitioned the slope of the TEE-BEE relationship (while accounting for sex, age, FFM, FM, and sex- and age-related differences in FFM and FM) at the between- and within-individual levels (Table S2A). This analysis clearly reveals that energy compensation occurs only at the within-individual level (Figure 4A). While the between-individual slope was $b_{between} \pm SE = 1.86 \pm 1.05$, the within-individual slope was $b_{within} \pm SE = 0.15 \pm 0.17$.

To further illustrate the compensation occurring at the within-individual level, we ran a second bivariate mixed model with AEE and BEE as the dependent variables. In this model, the within-individual covariance was significantly negative (Table S2B). The within-individual correlation (±SE) between AEE and BEE was $r = -0.58 \pm 0.08$ (Figure 4B). Hence, during extended periods when the studied cohort expended more energy on activity, they compensated by reducing energy expended on basal processes (but individuals with higher-than-average AEE do not necessarily have a lower-than-average BEE). The within-individual slope in these people indicates particularly strong energy compensation between AEE and BEE (Figure 4B). That is, in this sample of people, the calories they burn during bouts of activity are almost entirely compensated for by reducing energy expended on other processes such that variation in activity had little impact on TEE.

Measurements of BEE and TEE provide invaluable insights into energy management; the next step is to elucidate the proximate and ultimate mechanisms driving these observed patterns of energy compensation. One possible factor is energy intake. For example, if obese people tend to increase their food consumption in response to increased AEE less so than other demographics, they have fewer resources for other functions, and this could encourage the body to energy compensate, reducing BEE.[31] Another possible factor involved in energy compensation, which is relatively hard to measure and not available in our dataset, is fidgeting, or non-exercise activity thermogenesis (NEAT). In principle, NEAT can decrease in response to increases in AEE, although few studies have directly measured it,[6] and reviews of the literature to determine whether NEAT in humans decreases to compensate or partially compensate for increases in AEE conclude that there is no evidence overall that NEAT systematically changes, e.g., Fedewa et al.[5]

If energy compensation has an underlying genetic basis, in the future it might be possible to screen individuals to ascertain whether exercise would be a valuable fat loss intervention because they are "weak compensators" or a fruitless fat loss intervention because they are strong compensators (while recognizing other benefits to exercise including protecting against weight regain[32,33]). Moreover, we need to understand whether there are costs to reducing BEE. If there are, such as, for example, a compromised immune system or slowed recovery from injury,[34,35] then for some individuals the point at which exercise reaches a detrimental level will be considerably lower than for others.

The ever growing and diversifying range of fat loss plans and fads available to the public reflects the reality, well known to researchers, that prescribed exercise programs for weight reduction rarely result in substantive or long-term changes in body mass.[36] The few national guidelines that have been published converge on the recommendation of a 500–600 kcal/day deficit through exercising and dieting to instigate fat loss.[37] These guidelines are general for the population and do not factor in the variation in energy compensation exhibited by people with different levels of fat mass, as demonstrated in the current study. Public health strategies for fat loss should be revised to recognize energy compensation as our understanding progresses about which individuals compensate and by how much. In this vein, more research is needed on the potentially substantial diversity of energy compensation between sub-populations. In the future, personalized exercise plans targeting fat loss might be developed partly based on an individual's genetic propensity for energy compensation.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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- RESOURCE AVAILABILITY
  - Lead Contact

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.cub.2021.08.016.

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AUTHOR CONTRIBUTIONS

V.C. and L.G.H. suggested the idea of testing for energy compensation in the available dataset, undertook analyses, and led on the manuscript writing. J.R.S. contributed to manuscript writing. All authors apart from L.G.H. and V.C. provided DLW data to the database that was used in the analyses, read the manuscript, and commented if they wished. J.R.S., C.L., A.H.L., A.J.M.-A., H.P., J.R., D.A.S., H.S., K.R.W., W.W.W., and Y.Y. assembled and manage the database.

DECLARATION OF INTERESTS

The authors have no conflicts of interest to declare.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
Custom-written R code (script) for the analysis and generation of data figures.	Custom-written by the authors.	Figshare. Entitled 'R script for Current Biology paper 'Energy compensation and adiposity in humans': https://figshare.com/articles/software/R_script_for_Current_Biology_paper_Energy_compensation_and_adiposity_in_humans_/15054129

RESOURCE AVAILABILITY

Lead Contact

Further information and requests should be directed to and will be fulfilled by the lead contact, Lewis Halsey (l.halsey@roehampton.ac.uk).

Materials availability

All the data used in this study have already been published and are available in the public domain; the current manuscript presents a secondary analysis.

Data and code availability

- The data reported in this study cannot be deposited in a public repository because they are held by the management group of the IAEA DLW database. To request access, follow the instructions available at https://doubly-labelled-water-database.iaea.org/dataAnalysisInstructions.
- The code used for all statistical analyses and the production of data figures has been deposited at Figshare and is publicly available as of the date of publication. The DOI is listed in the key resources table.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND SUBJECT DETAILS

The International Atomic Energy Agency DLW database (v 3.1.2) is a world-wide collection of total energy expenditure (TEE) measurements.[20] All TEE measurements were made using the stable isotope method of doubly-labeled water analysis,[14,38] and are based on recalculations of the original data using the latest DLW equations.[21] Although the entire database includes over 6,500 DLW measurements between 1981 and 2017, for the purpose of this study the database was restricted to TEE measures accompanied by measurements of BEE via indirect calorimetry. The database was also restricted to adult subjects (> 18 y old) and we excluded subjects undergoing intense physical activity including professional sports training, and those who were pregnant, lactating, or diseased. Fat free (lean) mass (FFM) was derived from isotope dilution and fat mass (FM) was calculated by subtracting FFM from total body weight. Note that using total body weight and height-normalized indices of FFM and FM yielded similar results to using FFM and FM. Activity energy expenditure (AEE) was calculated as 0.9*TEE – BEE, assuming that the thermic effect of food accounts for 10% of the total energy budget.[39] The average (±SD) physical activity level (PAL = TEE/BEE) of the analyzed database was 1.74 ± 0.27 (range: 0.76 – 3.30) and 90% of observations were between 1.35 and 2.18 PAL (5^{th} and 95^{th} quartiles).

METHOD DETAILS

To test the mutually exclusive predictions arising from the energy management models (Figure 1C), we used multiple linear regressions with TEE as the dependent variable and sex, age, FFM, FM, and BEE as independent variables, on some or all of a dataset on 1754 adults. FFM and FM were square-root transformed to reduce the influence of some potentially influential observations at the extreme upper end of the distribution (e.g., 6 observations with > 80 kg fat mass).

QUANTIFICATION AND STATISTICAL ANALYSIS

All analyses were conducted in R using bespoke code. Details of the results of those analyses are found in the Results and discussion section, and the Tables S1 and S2, with visualization provided in Figures 2, 3, and 4. Confidence intervals are provided for all regression slope estimates. Results were interpreted as statistically significant when associated with $p < 0.05$. The first multiple regression model was run on the entire dataset to get an overall estimate of the TEE-BEE and AEE-BEE relationships after accounting for sex, age, FFM, and FM (Table S1A). We were then interested to test if the TEE-BEE and AEE-BEE relationships varied by sex, age, and body composition. To do so, we introduced two-way interactions between BEE and sex, age, FFM, and FM (Table S1B). To control for possible sex- and age-related changes in the effects of FFM and FM, we also included two-way interactions between body composition variables (FFM and FM) and sex and age (Table S1B). All independent variables (including sex) were centered prior to analysis, such that significance of main effects are estimated at the average values despite significant interactions in the model.[40] We used the visreg function[41] to plot the partial residuals and illustrate the TEE-BEE and AEE-BEE slopes (Figure 2) and the interaction between BEE and FM (Figure 3). For these models, the residuals had homogeneity of variance and were normally distributed, and there were suitably low variance inflation factors for all covariates indicating limited linear covariance between the predictor variables.[42]

Bivariate mixed model analysis

The Health, Aging, and Body Composition (Health ABC) study has produced repeated paired measurements of TEE and BEE in elderly men and women.[43] The first set of measurements were taken between 1998 and 2000 on subjects in their 8th decade of life. A second set of measurements was carried out in 2006, approximately 7 years after the first.[30] We used bivariate mixed models in ASReml-R[44] to partition the relationship between TEE and BEE at the between- versus within-individual levels in men and women separately. Both TEE and BEE were fitted as response variables in a model that included (anonymous) individual identity as a random effect. This enabled modeling of the between-individual variances ($V_{between}$) in TEE and BEE as well as the between-individual covariance ($COV_{between}$) between the two. The residuals were also modeled as an unstructured variance-covariance matrix, effectively capturing the within-individual variances (V_{within}) in TEE and BEE as well as the within-individual covariance (COV_{within}). The between-individual slope ($b_{between}$) between TEE and BEE was calculated as $COV_{between}$ divided by $V_{between}$ in BEE, while the within-individual slope (b_{within}) was calculated as COV_{within} divided by V_{within} in BEE. Note that the bivariate mixed model included age, FFM, and FM as fixed effects fitted to both TEE and BEE, and as such the slope estimates are conditioned on these variables. Moreover, interactions between age and FFM and age and FM were included to control for potential age-related changes in body composition. To better illustrate the relationship between AEE and BEE, we ran a second bivariate mixed model that was identical to the above except that TEE was replaced by AEE. For each model, assessment of the residuals indicated homogeneity of variance and normality, and suitably low variance inflation factors for all covariates.