Prevalence and characteristics of energy intake under-reporting among Australian adults in 1995 and 2011 to 2012

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Prevalence and characteristics of energy intake under-reporting among Australian adults in 1995 and 2011-12

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ABSTRACT

Aim: Misreporting of energy intake is a common source of measurement error found in dietary surveys, resulting in biased estimates and a reduction in statistical power. This study aims to refine the conventional cut-off methods, to examine the extent to which Australian adults misreport their energy intake and the characteristics of under-reporters between two time points

Methods: An improved Goldberg cut-off approach was used to identify those who reported implausible intake amounts in large cross-sectional surveys. Identified low energy reporters were then used as the outcome variable in Poisson regressions to examine association with sex, age, BMI, weight perceptions, education, relative household income, geographic remoteness, and relative socioeconomic disadvantage.

Results: The prevalence of under-reporting increased from 32% in 1995 to 41% in 2012, most of which can be attributed to an increase in men. Under-reporting has a positive association with BMI and relative socio-economic disadvantage, but an inverse association with age, education, relative household income and residence in inner regional areas.

Conclusions: Under-reporting of energy intake is high in Australian adults, and appears have worsened over time in men, which could be partly explained by the upward trend in obesity. The use of conventional Goldberg methods to identify under-reporters can significantly underestimate the prevalence of under-reporting, future studies should consider selecting a lower critical value to improve accuracy.

Key words: Dietary assessment, dietary intake, methodology, adults, obesity, dietary intake data

INTRODUCTION

In dietary measurement, people tend to report values lower than their actual energy intake.[1] This under-reporting may be due to intentional and unintentional reasons including social pressure, inconvenience, poor memory, poor attention, and a lack of comprehension.[2] It could also be the result of dieting or undereating influenced by the dietary assessment process.[3] Accounting for sex, age, and body mass, basal metabolic rate (BMR) prediction equations can be used estimate a person's baseline rate of metabolism at rest with a fair amount of accuracy. One can then statistically determine whether an individual is likely to be under-reporting by comparing their energy intake as a multiple of their BMR (Goldberg method);[4] or as a multiple of their estimated energy requirement (EER).[5] Once these individuals are identified, the bias due to under-reporting can be addressed by excluding these implausible reporters, although exclusion may lead to selection bias; or by the use of statistical techniques that adjust for total caloric intake, dietary composition, or the energy density of nutrients.[1, 6]

The monitoring of energy intake and energy expenditure can be done by instruments or surveys and interviews. Examples of instrument-based monitoring include direct observation and photographic methods for dietary intake;[7] indirect calorimetry, doubly labelled water (DLW), and accelerometry for energy expenditure.[8] As instrument-based measurements may not be financially feasible on a sufficiently large scale, surveys are often used to measure the dietary and physical activity changes in the population for the development and evaluation of food and nutrition policies and interventions. Non-instrument based methods include food records, food frequency questionnaires, and 24-hour recalls for dietary intake; and activity diaries, physical activity questionnaires and interviews for energy expenditure.[8, 9] However, self-reporting can introduce bias, and misreporting of energy intake is a common source of measurement error found in dietary surveys.[10] While over-reporting is generally less problematic in adults than in children,[11] bias caused by under-reporting is certainly a concern and can be extremely difficult to eliminate without the use of more expensive means of obtaining instrument-based measures.[12]

The objective in this study is to refine the existing conventional methods to improve their accuracy, to estimate the level of misreporting of food intake in the Australian adult population for 1995 and 2011-12, and to examine the characteristics of under-reporters in particular. Few studies have looked at energy under-reporting in Australia, especially adults at the national level.[13-16] Understanding the characteristics and predictors of under-reporting will help ascertain what makes them different from accurate reporters. Moreover, the amount of energy that is required for each individual to reach neutral energy balance can be reconstructed in future studies based on these refined methods to model health impact assessment of weight loss interventions.

METHODS

The 1995 National Nutrition Survey (NNS) and 2011-12 National Nutrition and Physical Activity Survey (NNPAS) from the Australian Bureau of Statistics (ABS) were used in this study, which had a response rate of 61% and 77% respectively.[17, 18] Due to the use of secondary confidentialised data, ethical approval was not required. Households were selected at random using a stratified three-stage area sample. Individuals below 18 years of age and those who were pregnant were excluded from the analysis. 11% and 67% of these individuals from 1995 NNS and 2011-12 NNPAS respectively participated in a second 24-hour dietary recall. The selected sample used for analysis consisted of 1,196 and 5,332 individuals from the two periods. Energy intake was reported via face-to-face 24-hour dietary recall, with pen and paper in 1995 and computer-based in 2011-12. The interviews were more or less evenly distributed in all four seasons. In terms of day of the week, Monday to Thursdays were equally frequent; the frequency decreased incrementally from Friday to Sunday. The 1995 NNS employed a three-pass method whereas and 2011-12 NNPAS employed an automated five-pass method, both developed by United States Department of Agriculture Agricultural Research Service.[19]

In the 2011-12 NNPAS dataset, information on physical activity in the week before the interview was also recorded, which included walking of 10 minutes' duration or more, moderate activity, and vigorous activity. The questionnaire was based on the Active Australia Survey, which has been shown to be reliable and valid.[20-22] Duration and activity's intensity level (Metabolic Equivalent of Task, or MET) were then used to calculate MET minutes. ABS classifies physical activity into four categories, based on total MET minutes per week and whether respondents had more than an hour of vigorous activity. It should be noted that no information on physical activity is available from the 1995 NNS data. There is also dissimilar information on education and geographical areas from the two datasets. Education was converted from the different levels to number of years, ranging from 8 years to 16 years. Certificates III/IV add one year to schooling; other certificates add half a year; diplomas, Bachelor's degree, and postgraduate degree are coded as 14, 15, and 16 years of education respectively. Household income and socioeconomic disadvantage were categorised into quintiles. Higher quintiles denote that the individual lives in an area with less socioeconomic disadvantage.

Energy misreporters were identified using the Goldberg cut-off methods.[1, 4] An alternative method based on the ratio of EI to EER was used for comparison.[5] The Schofield prediction equations were used to estimate BMR for each individual based on their age, sex, weight, and height.[23] Schofield equations have been used in the original Goldberg study and have almost been exclusively used in the literature since then, therefore they were used even though there are newer BMR prediction equations available.[24] The critical values of 1.23 and

1.35 were applied to both Goldberg and EER methods, for men and women respectively, in order to improve sensitivity without forgoing much specificity. More details of the Goldberg and EER methods, and modifications to the default critical values are included in the Appendix.

The likely under-reporters and likely acceptable reporters, identified by the modified Goldberg method, then formed the outcome variable in a modified Poisson regression model to analyse demographic characteristics.[25] As under-reporting is common (greater than 10%), the odds ratios in logistic regression cannot be interpreted as an approximation of relative risks without correction.[26] Direct methods such as a log-binomial regression or a modified Poisson regression with robust error variances are recommended to estimate relative risk adjusting for covariates.[27] Predictor variables in these models included age, sex, body mass index (BMI) categories, weight perceptions, education, relative household income, geographical area (as defined by the Australian Statistical Geography Standard (ASGS) remoteness structure), and relative socioeconomic disadvantage (as defined by the Index of Relative Socio-Economic Disadvantage in Socio-Economic Indexes for Areas (SEIFA)).

RESULTS

Table 1: Estimated prevalence of under-reporting

Table 1 shows that the estimate for the prevalence of under-reporting has increased from 32% in 1995 to 41% in 2012, using a comparable method (constant cut-off). This increase is mostly due to an increase in men whereas under-reporting in women has hardly changed between the two periods. Over-reporting, on the other hand, does not appear to be a problem. It was estimated to be 1-2% in this study; however its accuracy is rather questionable with a significantly lower sensitivity, 0.1-0.2, despite very high specificity.[28]

Table 2: Risk of under-reporting of energy intake by sex in 2011-12 NNPAS

The multivariable Poisson regression results modelled separately for men and women are shown in Table 2, with the risk of low energy reporting as the outcome, identified using Goldberg (BMR method with variable cut-off) and Schofield with weight only. When adjusted for age, individuals of either sex with overweight were about 50% more likely and individuals with obesity are twice as likely to under-report their EI, compared to those with normal weight. Weight perceptions are no longer statistically significant after including for BMI categories as a covariate, but underweight perception has a 0.76 (p-value = 0.02) in the multivariable model that pooled both sexes in Table A4, which means doubling the sample size makes a difference for this category. When compared with the reference group, a lower risk of under-reporting was associated with being aged 60 or over and living in inner regional Australia. A 3-4% lower risk of under-reporting was also observed in higher education, higher household income and less socioeconomic disadvantage, but only for women not men highlighting sex-specific effects.

Notably, residence in an inner regional Australia has stayed highly statistically significant throughout. Including all other predictor variables did not change the inverse association between inner regional Australia and misreporting; it even increased the magnitude of the coefficient estimate slightly to 0.84 (p-value < 0.01) for women from 0.89. Individuals who lived in inner regional areas tended to be male, older, heavier, less educated, have a lower household income, and live in more socioeconomically disadvantaged areas, but all these characteristics except sex and age had a positive relationship with EI under-reporting. Besides, age and sex were already adjusted for as covariates. This result could be explained by a difference in attitude, perhaps due to more social acceptance or less peer pressure, in those living in inner regional areas as opposed to major cities and more remote areas.

Table 3: Risk of under-reporting of energy intake by sex in 1995 NNS and 2011-12 NNPAS

Table 3 shows the sex-specific multivariable models on data from the 1995 NNS and 2011-12 NNPAS, with the outcome still being the risk of low energy reporting, but identified using the constant cut-off Goldberg approach. This is because no information on physical activity was available in the 1995 NNS data to categorise individuals into various PAL groups for the variable cut-off approach. The age, sex, and BMI variables were included into the model similar to the multivariable models in Table 5.

The risk when adjusted for age and BMI was 60% higher in 2012 than in 1995, consistent with the crude estimate of 70% (from 24.1% to 40.9%) indicated Table 1. On the other hand, there has been no change for women during the same period. The risk in higher BMI categories increased due to the inclusion of the 1995 NNS data. Overall, the rest of the results for 2011-12 are comparable to the results in Table 5. The only exception is when only data from 1995 were modelled; older age groups had higher under-reporting risk, though this was not observed when 2011-12 data were included as well (See A5 & A6 in the Appendix).

In order to understand how much a variable improved the goodness of fit of the models shown in Table 5, a pseudo R^2 could be computed for each variable in the single-variable case.[29] The Cox-Snell R^2 was 0.034 for BMI, and 0.017 for weight perceptions while it was less than 0.004 for other predictor variables. Adding age and sex to the model in addition to BMI increased the R^2 to 0.040, but very little further increase was gained by adding weight perceptions. Moreover, one could examine the changes to the relative risk of the period effect in the model shown in Table 6, by removing the BMI variable to understand the extent to which the increase in under-reporting risk over time in men is attenuated by keeping BMI constant. The period effect decreased from a relative risk of 1.70 to 1.60 after controlling for BMI.

DISCUSSION

Our study identified low energy reporters by applying an improved Goldberg method on two Australian national surveys, described the characteristics of these low-energy reporters, analysed these characteristics as predictors of under-reporting, and compared the risk of under-reporting between two time points. Under-reporting has increased for men from 1995 to 2012, and its prevalence could, in theory, be as high as over 50%. The increase in under-reporting over time could be partly explained by a more obese population, as higher BMI categories are consistently associated with higher risk of under-reporting regardless of model specification or time period. However, it is uncertain why this increase was mostly found in men and not women. Furthermore, under-reporting was associated with other characteristics such as younger age, lower education, lower relative household income, living in a socioeconomic disadvantaged area, and residence in a major city as opposed to inner regional areas. Weight perceptions were not linked to under-reporting when adjusted for BMI categories, as was the case in other studies; or there was a small residual effect in overweight perception depending on the model specification.[30, 31]

The 1995 prevalence estimates for under-reporting in energy intake in Australian adults were comparable to estimates for other countries, such as New Zealand, United States, Ireland, France, Denmark, Jamaica, and South Korea,[31-37] between 20% and 35%, as high as over 40% in Britain, Norway and Sweden.[38-40] However, these estimates were expected to underestimate the true prevalence, as the Goldberg method using the default critical value of 1.96 can only identify up to about two thirds but not all of the under-reporters. The 2011-12 under-reporting prevalence estimates were nearly 50% for adults in Australia, but would be about 30% if default cut-offs were used instead. Likewise, the prevalence estimates went from 46% to 67% in the Swedish study by shifting the cut-off points.[40] In terms of the amount of EI underestimation, the figure of 19.4% is also in line with other studies.[10]

Under-reporting was more prevalent in women than in men in 1995, yet under-reporting in men has surpassed that in women by 2012. It is unlikely that the increase in under-reporting was primarily driven by the differences in dietary assessment methodology in the two surveys, as men and women would likely be affected in the same way. While under-reporting was also observed more frequently in adults compared to children and adolescents, there is generally less of a gender difference in youth.[11] For example, 5% of Australian children and adolescents were found to be low-energy reporters in 2007, and there is no apparent difference between boys and girls up to 13 years of age.[14] It appears this gender difference in adults has narrowed considerably between 1995 and 2012.

The revised Goldberg method with variable cut-offs, has been shown to be able to identify approximately three quarters of the under-reporters while the number of false positives remains low. That, coupled with more “optimal” critical values, in theory, can identify more than 80% of all under-reporters without compromising much on false negatives. It is because by reducing the critical value from 1.96 to somewhere between 1 and 1.4, the sensitivity of the method is further increased while keeping specificity high, by optimising the trade-off between sensitivity and specificity. However, due to the 1995 NNS data not containing information on energy expenditure, the variable cut-off method had to be replaced by the constant cut-off method. The constant cut-off method typically yields a lower sensitivity with the default critical value of 1.96, but using critical values between 1 and 1.4 has been able to identify substantially more under-reporters, albeit still less sensitive than the variable variant with calibrated critical values. Additionally, it may not be sufficient to establish any trend in under-reporting based on only two time points.

Although NNPAS contains information on physical activity, sedentary behaviour, and sleep, deriving PAL values for each individual is not straightforward because walking of duration under 10 minutes is not reported. If information on physical activity of shorter duration were available, this could potentially further increase the accuracy of the Goldberg approach, by more accurately classifying the individual into their corresponding PAL category and thus a more accurate cut-off for the individual. In addition, the variation factor could be updated with values more specific to the Australian adult population, to more accurately account for the variation in energy intake, basal metabolic rate, and physical activity. Arguably, further improvements to the Goldberg approach may only be marginal due to diminishing returns.

This study has made improvement on the identification of under-reporters by adjusting the critical value use for calculating the Goldberg and EER cut-offs. It highlights the prevalence of underreporting in energy intake in Australia and the characteristics of under-reporters, which helps understand the limitations of current dietary surveys and the need for adjustments. The use of conventional Goldberg methods to identify under-reporters can underestimate the prevalence of under-reporting, future studies should consider selecting a critical value between 1 and 1.4 instead of the default z-score for 95% confidence level.

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TABLE LEGENDS

FIGURE LEGEND

No table of figures entries found.

Table 1: Estimated prevalence of under-reporting

Year	Methods	Male	Female	All
1995	1. Goldberg, constant cut-off	24.1%	39.6%	32.0%
2011-12	1. Goldberg, constant cut-off	40.9%	40.1%	40.5%
	2. Goldberg, variable cut-off	52.7%	44.1%	48.1%
	3. EER	50.5%	44.0%	47.1%

BMR is determined by Schofield (weight only) equations. EI is the average of two-day data. The critical values for the BMR-based methods are 1.23 and 1.35 for males and females, instead of 1.96 (95% confidence level).

Table 2: Risk of under-reporting of energy intake by sex in 2011-12 NNPAS

	Multivariable, Male					Multivariable, Female				
	RR	SE	P-value	95% CI		RR	SE	P-value	95% CI	
Age										
20-39	Reference					Reference				
40-59	0.98	0.04	0.62	0.90	1.06	0.89	0.04	0.02	0.81	0.98
60+	0.80	0.04	<0.01	0.73	0.88	0.79	0.04	<0.01	0.72	0.88
BMI Category										
Underweight	0.33	0.18	0.04	0.11	0.95	0.72	0.18	0.18	0.44	1.17
Normal weight	Reference					Reference				
Overweight	1.49	0.09	<0.01	1.33	1.67	1.45	0.08	<0.01	1.29	1.62
Obese	1.95	0.11	<0.01	1.75	2.18	2.00	0.10	<0.01	1.81	2.22
Perceived Weight										
Underweight	0.80	0.12	0.13	0.60	1.06	0.72	0.15	0.12	0.47	1.08
Acceptable	Reference					Reference				
Overweight	1.06	0.05	0.17	0.97	1.16	0.99	0.06	0.86	0.89	1.11
Education										
Years of education	1.01	0.01	0.15	1.00	1.03	0.96	0.01	<0.01	0.94	0.98
Household Income										
Quintiles	0.99	0.01	0.43	0.96	1.02	0.96	0.02	0.01	0.93	0.99
Geographical Areas										
Major cities	Reference					Reference				
Inner regional	0.89	0.04	0.02	0.80	0.98	0.89	0.05	0.03	0.80	0.99
Other	0.96	0.05	0.42	0.87	1.06	0.95	0.05	0.37	0.85	1.06
Social Disadvantage										
Quintiles	1.01	0.01	0.57	0.98	1.03	0.97	0.01	<0.05	0.95	1.00

RR, relative risk; SE, standard error; CI, confidence interval. The outcome is low energy reporter status identified using Goldberg (BMR, constant cut-off) and Schofield with weight only. Poisson regression modified with robust error variances is used, which includes age groups and BMI categories in addition to the variable of interest. The coefficient estimates for age groups and BMI categories are estimated together without any other variable. There are 2,512 and 2,820 observations for men and women respectively except for the perceived weight (2,509/2,819) and household income (2380/2600). Social disadvantage (SEIFA) is grouped such that higher quintiles denote less disadvantage.

Table 3: Risk of under-reporting of energy intake by sex in 1995 NNS and 2011-12 NNPAS

	Multivariable, Male, 1995 & 2012					Multivariable, Female, 1995 & 2012				
	RR	SE	P-value	95% CI		RR	SE	P-value	95% CI	
Age										
20-39	Reference					Reference				
40-59	1.09	0.06	0.10	0.98	1.21	0.99	0.05	0.77	0.90	1.08
60+	0.89	0.05	0.06	0.79	1.00	0.89	0.05	0.03	0.80	0.99
BMI Category										
Underweight	0.46	0.25	0.16	0.16	1.35	0.75	0.19	0.26	0.46	1.24
Normal Weight	Reference					Reference				
Overweight	1.71	0.13	<0.01	1.48	1.97	1.54	0.09	<0.01	1.38	1.72
Obese	2.74	0.20	<0.01	2.38	3.16	2.20	0.11	<0.01	1.98	2.44
Perceived Weight										
Underweight	0.82	0.15	0.27	0.57	1.17	0.68	0.15	0.07	0.44	1.03
Acceptable	Reference					Reference				
Overweight	1.15	0.06	0.01	1.03	1.28	1.06	0.06	0.33	0.95	1.18
Household Income										
Levels	0.95	0.02	<0.01	0.92	0.98	0.94	0.02	<0.01	0.91	0.97
Social Disadvantage										
Quintiles	0.99	0.02	0.42	0.96	1.02	0.97	0.01	0.02	0.94	0.99
Period										
1995	Reference					Reference				
2011-12	1.60	0.12	<0.01	1.38	1.86	0.97	0.05	0.62	0.88	1.08

RR, relative risk; SE, standard error; CI, confidence interval. The outcome is low energy reporter status identified using Goldberg (BMR, constant cut-off) and Schofield with weight only. Poisson regression modified with robust error variances is used, which includes age groups, BMI categories, and the period variable in addition to the variable of interest. The coefficient estimates for age groups, BMI categories, and the period variable are estimated together without any other variable. There are 3096 and 3432 observations for men and women respectively except for perceived weight (3092/3431), household income (2896/3139), socioeconomic disadvantage (3092/3427). Social disadvantage (SEIFA) is grouped such that higher quintiles denote less disadvantage.

APPENDIX

The Goldberg method is a conventional approach used to evaluate energy misreporting in a study population at the individual level, when non-instrument-based dietary assessments are conducted instead of instrument-based measures. It is based on the ratio of EI to BMR, and has two variants – constant cut-off and variable cut-off. For constant cut-off, the entire population was assumed to have an expected physical activity level (PAL) of 1.55, which is the probable minimum energy requirement for a sedentary population.[1] For the variable cut-off method, the population was divided into four PAL groups as defined by ABS. (ABS defines the PAL groups as follows: sedentary – less than 50 MET minutes a week; low – 50 to less than 800 MET minutes a week; moderate – 800 to 1600 MET minutes a week or over 1600 MET minutes but less than 1 hour of vigorous physical activity per week; high – over 1600 MET minutes a week and at least 1 hour of vigorous physical activity per week.[2]) This is to improve the identification of under-reporters by comparing an individual's reported energy intake with the expected energy requirement specific to their PAL level. The PAL values derived using regression results from Thompson et al.[3] are by and large concordant with the expected PAL values given by FAO/WHO/UNU[4] for each PAL category (See Table A1 in the Appendix). However, only the constant cut-off method could be used for the 1995 data due to a lack of information on the participants' PAL.

Table A1: Comparison of expected PAL from FAO/WHO/UNU and mean empirical PAL

	PA category	PAL (FAO/WHO/UNU)	Empirical PAL
Male	Low/Sedentary	1.55	1.48
	Moderate	1.78	1.77
	High	2.1	2.27
Female	Low/Sedentary	1.56	1.46
	Moderate	1.64	1.66

	High	1.82	1.95

Empirical PAL values for each individual are derived from the total minutes of moderate-vigorous activity per week in bouts of 10 minutes or more, taking the arithmetic mean of two equations shown in the additional file in Thompson, Batterham [3] that describe their relationship. $\mathrm{PAL} = ((\mathrm{Time} + 1133)/814 + (\mathrm{Time} + 2556)/1851)/2$

The Goldberg Method

When weight is stable, energy intake is equal to energy expenditure. If both terms are expressed as multiples of BMR, the following equation ensues.

$$\frac{EI}{BMR} = \frac{EE}{BMR} \tag{1}$$

PAL can be defined as EE divided by BMR ($PAL = \frac{EE}{BMR}$). The Goldberg cut-off method is used to estimate whether an individual is likely to be misreporting their energy intake, by way of comparing their EI as a multiple of BMR against their expected PAL.

Upper or lower confidence bounds for the Goldberg method were calculated as follows:

$$upper/lower\ limit = PAL \times e^{z \times \frac{S}{\sqrt{n}}} \tag{2}$$

where z is ± 2 for 95% confidence level, n is the number of subjects in the study (for individual-level identification, n is 1), S is a variation factor which takes into account the within-subject daily variation in energy intake (${CV_{wEI}}^2$), within-subject variation in basal metabolic rate (${CV_{wB}}^2$), and total variation in physical activity (${CV_{tP}}^2$), as well as the number of days of diet measurement (d), as expressed below.

$$S = \sqrt{\frac{{CV_{wEI}}^2}{d} + {CV_{wB}}^2 + {CV_{tP}}^2} \tag{3}$$

The values for these coefficients of variation were assumed to be 23%, 8.5% (for estimated BMR), and 15% respectively as suggested in the literature and widely used in other studies to identify energy misreporting.[5, 6] For example, the lower cut-off value for EI:BMR with a mean PAL of 1.55 is 0.87[‡] for a single day of dietary record. In other words, if the reported energy intake is below 0.87 for a given individual, he or she is likely to be an under-reporter, also known as a low energy reporter (LER). Furthermore, the cut-off values can

‡ $PAL \times e^{z \times \frac{S}{\sqrt{n}}} = PAL \times e^{z \times \frac{\sqrt{\frac{{CV_{wEI}}^2}{d} + {CV_{wB}}^2 + {CV_{tP}}^2}}{\sqrt{n}}} = 1.55 \times e^{-2 \times \frac{\sqrt{\frac{23\%^2}{1} + 8.5\%^2 + 15\%^2}}{\sqrt{1}}} = 0.8723$

depend on the expected PAL value of a specific PAL category in the case of the variable PAL variant.

<u>The EER method</u>

$$EI = EER \tag{4}$$

Alternatively, EER equations can be used to estimate the energy expenditure, and therefore be used instead of BMR in the Goldberg cut-off method.[7] EER equations are specific to age, sex, and BMI categories.[8] The ratio between EI and EER is expected to be 1 at energy balance, so the PAL term in Equation 2 is replaced by the value 1, as follows.

$$upper/lower\ limit = 1 \times e^{z \times \frac{S}{\sqrt{n}}} \tag{5}$$

The new variation factor S is similar to Equation 3 but specific to EER instead of BMR, taking into account the within-subject daily variation in energy intake ($CV_{wEI}{}^2$), the error in the EER equations ($CV_{eEER}{}^2$), and the daily variation in total energy expenditure ($CV_{tEE}{}^2$), as well as the number of days of diet measurement (d), as expressed below.

$$S = \sqrt{\frac{CV_{wEI}{}^2}{d} + CV_{eEER}{}^2 + CV_{tEE}{}^2} \tag{6}$$

The values for CV_{wEI}, CV_{eEER}, and CV_{tEE} were assumed to be 23%, 11%, and 8.2% respectively.[7] The lower cut-off value for EI:EER for men is 0.72 with two days of food records, and that for women is 0.70.

While the PAL value 1.55 has been recommended by FAO/WHO/UNU (1985) to be the energy requirement for a sedentary/lightly active population, it was found to be conservative by subsequent DLW studies.[9] Black also found that increasing the constant cut-off from 1.55 to 1.65-1.95 traded specificity for higher sensitivity, with the marginal gain in sensitivity decreasing quite sharply after 1.75.[5] Nonetheless, one could argue that adjusting the mean to improve sensitivity may not be statistically valid.

The default critical value (z-score) of 1.96 generally results in a sensitivity of about 0.5 for constant cut-off, a sensitivity of about 0.7 for variable cut-off, and a specificity of over 0.95 for both Goldberg variants.[5] However, it has been suggested that reducing the critical value to between somewhere 1 and 1.4 to identify the maximum number of implausible reporters while maintaining biological plausibility.[7] The critical value was calibrated in order to improve sensitivity to over 0.8 and specificity of about 0.9, based on the estimated trade-off relationship between sensitivity and specificity from a 2012 US study that examined the accuracy of the Goldberg method on 2-day 24-hour dietary recall.[10] The calibration procedure involved selecting cut-off values near the point at which sensitivity and specificity intersect. Whether the underreporting prevalence estimate is underestimated or overestimated depends on what the true prevalence around which the selection is centred. The assumed true prevalence was centred at approximately 38% for men and 33% for women. The critical values were determined to be 1.23 and 1.35 for men and women respectively, applied to both Goldberg and EER methods. The different cut-off values for low, moderate, and high physical activity categories are shown in Table A2.

Table A2: Lower and upper Goldberg variable cut-off values for each physical activity category

	PA category	PAL*	Lower cut-off	Upper cut-off
Male	Low/Sedentary	1.55	1.16	2.07
	Moderate	1.78	1.33	2.38
	High	2.1	1.57	2.81
Female	Low/Sedentary	1.56	1.13	2.15
	Moderate	1.64	1.19	2.26
	High	1.82	1.82	2.51

* PAL values from FAO/WHO/UNU, 1985.[4] Cut-off values calculated assuming CV_{wB} 8.5%, CV_{wEI} 23%, CV_{tP} 15 % and using 2-day dietary records for a single individual. Critical values are 1.23 (male) and 1.35 (female).[5, 6]

Table A3: Descriptive statistics of individuals with 2-day dietary data in 2011-12 NNPAS

	Male									Female								
		EI		EER		EI:EER		% LER			EI		EER		EI:EER		% LER	
	n	Mean	SD	Mean	SD	Mean	SD	Mean	SD	n	Mean	SD	Mean	SD	Mean	SD	Mean	SD
All	2512	9609	3004	12376	2295	0.795	0.264	0.527	0.499	2820	7385	2374	9267	1586	0.815	0.283	0.441	0.497
Age																		
20-39	877	10241	3090	13496	2270	0.779	0.265	0.523	0.500	909	7688	2486	10093	1457	0.779	0.282	0.458	0.498
40-59	894	9683	3072	12503	2066	0.791	0.269	0.573	0.495	1013	7500	2407	9441	1403	0.809	0.280	0.448	0.498
60+	741	8772	2597	10897	1712	0.819	0.255	0.475	0.500	898	6947	2149	8237	1322	0.859	0.283	0.416	0.493
BMI Category																		
Underweight	24	10453	679	10783	389	0.984	0.065	0.125	0.069	55	8227	408	8324	170	0.996	0.049	0.236	0.058
Normal weight	697	10184	122	11705	84	0.884	0.011	0.366	0.018	1131	7604	71	8848	43	0.876	0.009	0.321	0.014
Overweight	1100	9570	87	12347	66	0.790	0.007	0.534	0.015	848	7315	78	9197	52	0.808	0.009	0.449	0.017
Obese	691	9062	109	13153	87	0.705	0.009	0.692	0.018	786	7084	85	10012	58	0.722	0.009	0.620	0.017
Perceived Weight																		
Underweight	123	10113	322	11012	198	0.929	0.028	0.293	0.041	91	7702	281	7725	138	1.003	0.035	0.220	0.044
Acceptable	1277	9941	86	12189	65	0.833	0.007	0.464	0.014	1380	7496	64	8963	40	0.852	0.008	0.372	0.013
Overweight	1109	9174	84	12749	65	0.736	0.007	0.626	0.015	1348	7250	64	9684	43	0.765	0.007	0.527	0.014
Education																		
< Year 12	620	9249	121	11470	85	0.824	0.011	0.490	0.020	951	6929	73	8676	51	0.819	0.009	0.475	0.016
Year 12 or equivalent	980	9702	98	12502	74	0.795	0.009	0.527	0.016	753	7481	87	9586	55	0.795	0.010	0.467	0.018
Diploma	257	9299	171	12552	142	0.757	0.015	0.576	0.031	321	7514	138	9447	85	0.815	0.016	0.433	0.028
Bachelor Degree	426	10164	179	13132	109	0.774	0.012	0.570	0.024	545	7884	121	9563	64	0.831	0.013	0.398	0.021
Postgraduate Degree	229	9922	191	12683	138	0.795	0.016	0.489	0.033	250	7860	138	9684	91	0.831	0.017	0.336	0.030
Household Income																		
Lowest 20%	379	8704	145	11260	106	0.788	0.013	0.541	0.026	590	6898	96	8634	63	0.817	0.012	0.476	0.021
Second quintile	388	9466	145	11524	103	0.837	0.013	0.477	0.025	502	7132	98	8928	71	0.818	0.012	0.450	0.022
Third quintile	440	9591	136	12411	110	0.792	0.012	0.534	0.024	499	7637	107	9426	69	0.833	0.013	0.411	0.022
Fourth quintile	547	10132	136	12803	94	0.808	0.012	0.519	0.021	521	7656	103	9745	64	0.800	0.011	0.447	0.022
Highest 20%	626	9870	117	13102	87	0.771	0.010	0.545	0.020	488	7728	109	9824	65	0.803	0.012	0.414	0.022
Geographical Areas																		
Major cities	1642	9539	75	12490	57	0.781	0.006	0.538	0.012	1771	7333	55	9311	38	0.806	0.007	0.449	0.012
Inner regional	478	9866	136	12186	99	0.827	0.012	0.487	0.023	580	7548	100	9165	65	0.842	0.012	0.407	0.020
Other	392	9590	145	12130	117	0.811	0.013	0.526	0.025	469	7378	119	9228	75	0.816	0.014	0.452	0.023
Socio-Economic Areas																		
Most disadvantage	441	9317	147	11885	104	0.803	0.014	0.522	0.024	538	7107	106	9070	69	0.802	0.013	0.504	0.022
Second quintile	496	9524	134	12344	104	0.794	0.013	0.538	0.022	569	7363	99	9279	69	0.812	0.012	0.453	0.021
Third quintile	489	9650	136	12231	98	0.803	0.012	0.511	0.023	546	7552	110	9251	68	0.837	0.013	0.418	0.021
Fourth quintile	463	9936	145	12807	110	0.791	0.012	0.527	0.023	496	7170	98	9234	67	0.794	0.012	0.476	0.022
Least disadvantage	623	9608	113	12542	93	0.785	0.010	0.533	0.020	671	7648	87	9454	61	0.827	0.010	0.374	0.019

EI, energy intake; EER, estimated energy requirement; n, the number of observations; SD, standard deviation; % LER denotes the prevalence of low energy reporters, who have been identified using Goldberg (BMR, variable cut-off) and Schofield with weight only. The perceived weight and household income variables only have 5,328 and 4,980 observations respectively, while all other variables have 5,332.

Descriptive statistics are included in Table A3 in the Appendix. Men reported an average of 9609 kJ of daily EI, whilst their EER is 12376 kJ. Women reported an average of 7385 kJ of daily EI, whilst their EER is 9267 kJ. The average of 2-day dietary data reduces the daily EI to 97% of 1-day EI, and reduces the variance to 66% or standard deviation to 81% of 1-day EI (not shown). The mean EI:EER ratio is 0.80 for men and 0.82 for women. The ratio is considerably higher in normal-weight individuals at 0.88. Notably, underweight individuals reported their energy intake as much as their expected energy requirement, on average. On the other hand, individuals with obesity reported lower than average EI:EER ratio, only about 70% of the expected energy requirement has been reported. Likewise, perceived weight is inversely associated with EI:EER, where those who perceive themselves as underweight have the highest EI:EER, and vice versa.

The differences in mean EI:EER are less pronounced for the other variables, as the values range between 0.75 and 0.85. Among education groups in males, the mean EI:EER is similar, except for individuals who have not completed Year 12 or equivalent (those with a total of at least 12 years of education, but less than 14 years, were regarded as equivalent to Year 12) who have a higher average; in females, individuals who have university education have a higher mean EI:EER than those with less education. Individuals living in inner regional areas tend to have a higher EI:EER than other geographical areas.

The proportion of LER is progressively lower in older age group, while it is progressively higher in higher BMI categories and perceived weight categories ranging from about 20% in underweight and normal-weight categories to 65% in the obese category. The same relationship is observed in weight perceptions. The range is less extreme for the other predictor variables. In women, higher education, higher income and areas with less socio-economic disadvantage have lower proportion of LER, whereas in men, similar levels of LER are found.

Table A4: Risk of under-reporting of energy intake in 2011-12 NNPAS

	Single Variable					Multivariable				
	RR	SE	P-value	95% CI		RR	SE	P-value	95% CI	
Sex										
Men	1.19	0.03	<0.01	1.13	1.26	1.13	0.03	<0.01	1.07	1.20
Women	Reference					Reference				
Age										
20-39	Reference					Reference				
40-59	1.03	0.03	0.31	0.97	1.10	0.93	0.03	0.03	0.88	0.99
60+	0.90	0.03	<0.01	0.84	0.97	0.80	0.03	<0.01	0.74	0.86
BMI Category										
Underweight	0.60	0.14	0.02	0.38	0.93	0.59	0.14	0.02	0.38	0.93
Normal weight	Reference					Reference				
Overweight	1.47	0.06	<0.01	1.36	1.59	1.47	0.06	<0.01	1.36	1.60
Obese	1.93	0.07	<0.01	1.79	2.08	1.98	0.08	<0.01	1.84	2.14
Perceived Weight										
Underweight	0.63	0.07	<0.01	0.50	0.79	0.76	0.09	0.02	0.60	0.96
Acceptable	Reference					Reference				
Overweight	1.37	0.04	<0.01	1.30	1.45	1.03	0.04	0.43	0.96	1.10
Education										
Years of education	0.99	0.01	0.04	0.98	1.00	0.99	0.01	0.03	0.97	1.00
Household Income										
Quintiles	1.00	0.01	0.92	0.98	1.02	0.98	0.01	0.03	0.96	1.00
Geographical Areas										
Major cities	Reference					Reference				
Inner regional	0.90	0.03	0.01	0.83	0.97	0.89	0.03	<0.01	0.82	0.95
Other	0.99	0.04	0.72	0.91	1.06	0.96	0.04	0.23	0.89	1.03
Social Disadvantage										
Quintiles	0.98	0.01	0.01	0.96	0.99	0.99	0.01	0.30	0.97	1.01

RR, relative risk; SE, standard error; CI, confidence interval. The outcome is low energy reporter status identified using Goldberg (BMR, constant cut-off) and Schofield with weight only. Poisson regression modified with robust error variances is used. The multivariable model includes sex, age groups, and BMI categories in addition to the variable of interest. The coefficient estimates for sex, age groups, and BMI categories are estimated together without any other variable in the multivariable case. The coefficient estimates for sex, age groups, and BMI categories are estimated without any other variable. There are 5332 observations except for the perceived weight (5328) and household income (4980). Social disadvantage (SEIFA) is grouped such that higher quintiles denote less disadvantage.

Figure A1: Distribution of EI:EER in 2011-12 NNPAS

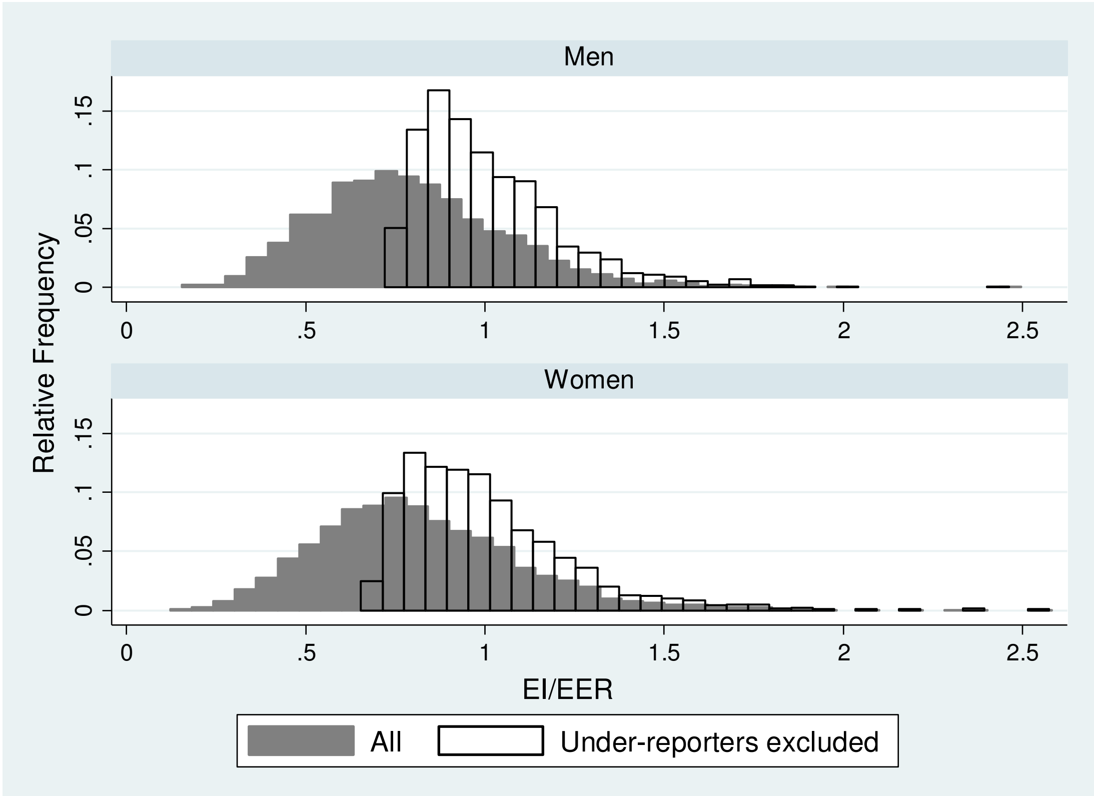

Figure A1 shows how the distribution of the EI:EER ratio changed when low-energy reporters (BMR, variable cut-off) were excluded from the sample. The mean increased to 1.01 and 1.00 for men and women respectively, which means on average these individuals report 100% of their EER in their EI. The minimum EI:EER is 0.65 (0.72 for men) which coincides with the cut-off threshold of the EER method which is 0.65 for two-day data, despite the fact that the variable BMR method was used instead.

The simple Poisson regression and Poisson regression adjusted for age, sex, and BMI produced generally comparable results as shown in Table A4. Men were 19% more likely than women to under-report, slightly reduced to 13% more likely when age and BMI were included as covariates. Furthermore, most estimates remained robust when BMI categories were included into the model along with age and sex in addition to the variable of interest. Mostly as a result of controlling for BMI, weight perceptions and socioeconomic disadvantage were no longer statistically significant. Age 40-59 is now statistically significant with a relative risk of 0.93, age 60 and over now has a lower relative risk of 0.8 as opposed to 0.9 in the univariable model.

Table A5: Risk of under-reporting of energy intake for men in 1995 NNS and 2011-12 NNPAS

	Multivariable, Male, 1995					**Multivariable, Male, 2012**				
	RR	SE	P-value	95% CI		RR	SE	P-value	95% CI	
Age										
20-39	Reference					Reference				
40-59	1.70	0.31	<0.01	1.19	2.43	1.02	0.06	0.68	0.92	1.14
60+	1.49	0.30	0.05	1.00	2.21	0.83	0.05	<0.01	0.74	0.94
BMI Category										
Underweight	NA	NA	NA	NA	NA	0.52	0.28	0.22	0.18	1.50
Normal Weight	Reference					Reference				
Overweight	1.59	0.35	0.04	1.03	2.45	1.71	0.13	<0.01	1.47	2.00
Obese	3.34	0.73	<0.01	2.18	5.12	2.65	0.20	<0.01	2.29	3.08
Perceived Weight										
Underweight	0.92	0.53	0.88	0.30	2.82	0.81	0.16	0.28	0.55	1.19
Acceptable	Reference					Reference				
Overweight	1.03	0.18	0.89	0.73	1.45	1.16	0.07	0.01	1.04	1.30
Household Income										
Levels	0.94	0.05	0.32	0.84	1.06	0.95	0.02	<0.01	0.92	0.98
Socioeconomic Areas										
Quintiles	1.03	0.05	0.58	0.93	1.14	0.98	0.02	0.23	0.95	1.01

RR, relative risk; SE, standard error; CI, confidence interval; NA, not available. Too few observations can result in an estimate of zero which is denoted by NA. The outcome is low energy reporter status identified using Goldberg (BMR, constant cut-off) and Schofield with weight only. Poisson regression modified with robust error variances is used, which includes age groups and BMI categories, in addition to the variable of interest. The coefficient estimates for age groups and BMI categories are estimated together without any other variable. There are 584 and 2512 observations for men in 1995 and 2011-12 respectively except for perceived weight (583/2509), household income (516/2380), and socioeconomic areas (580/2512). Socioeconomic areas (SEIFA) are grouped such that higher quintiles denote less disadvantage.

Table A6: Risk of under-reporting of energy intake for women in 1995 NNS and 2011-12 NNPAS

	Multivariable, Female, 1995					**Multivariable, Female, 2012**				
	RR	SE	P-value	95% CI		RR	SE	P-value	95% CI	
Age										
20-39	Reference					Reference				
40-59	1.46	0.18	<0.01	1.16	1.85	0.90	0.05	0.05	0.81	1.00
60+	1.27	0.17	0.07	0.98	1.65	0.83	0.05	<0.01	0.74	0.92
BMI Category										
Underweight	0.54	0.51	0.52	0.08	3.51	0.75	0.20	0.28	0.45	1.26
Normal Weight	Reference					Reference				
Overweight	1.79	0.23	<0.01	1.38	2.31	1.48	0.09	<0.01	1.30	1.67
Obese	2.44	0.31	<0.01	1.89	3.13	2.13	0.12	<0.01	1.91	2.38
Perceived Weight										
Underweight	NA	NA	NA	NA	NA	0.81	0.17	0.34	0.54	1.24
Acceptable	Reference					Reference				
Overweight	1.17	0.15	0.21	0.91	1.50	1.04	0.07	0.51	0.92	1.18
Household Income										
Levels	0.92	0.04	0.04	0.86	1.00	0.94	0.02	<0.01	0.91	0.97
Socioeconomic Areas										
Quintiles	1.01	0.04	0.73	0.94	1.08	0.96	0.01	0.01	0.93	0.99

RR, relative risk; SE, standard error; CI, confidence interval; NA, not available. Too few observations can result in an estimate of zero which is denoted by NA. The outcome is low energy reporter status identified using Goldberg (BMR, constant cut-off) and Schofield with weight only. Poisson regression modified with robust error variances is used, which includes age groups and BMI categories, in addition to the variable of interest. The coefficient estimates for age groups and BMI categories are estimated together without any other variable. There are 612 and 2820 observations for men in 1995 and 2011-12 respectively except for perceived weight (612/2819), household income (539/2600), and socioeconomic areas (607/2820). Socioeconomic areas (SEIFA) are grouped such that higher quintiles denote less disadvantage.

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