currently the source of much speculation with some researchers implicating genetic or physiological difference and others highlighting behavioural disparities in participants as the explanation. This study aims to identify the demographic and psycho-social characteristics associated with responders and non-responders to a range of weight loss regimens.

**Methods:** Two complementary approaches were employed. A systematic search was performed to identify any reported associations between socio-demographic factors and weight loss outcomes noted in published reports of clinical trials employing common weight loss approaches (e.g. low carbohydrate diets). These factors were then examined in existing clinical trial datasets from studies undertaken at the Boden Institute that utilised a variety of weight loss regimens including defined calorie deficit, high protein, and Korean diet substitution, to determine whether similar associations were observed.

**Results:** A range of social and demographic variables were identified in the literature review to influence variations in weight loss but analysis of existing datasets was less revealing. Preliminary analyses suggests that older individuals are more likely to comply and adhere to defined calorie deficit weight loss interventions but no consistent gender differences exist in weight loss outcomes from a range of different regimens. Limited studies show that Caucasians have greater weight loss success on defined calorie deficits compared to those of other ethnicity or mixed races.

**Conclusions:** Current assessments have not identified demographic or simple psycho-social factors that strongly predict greater or poorer response to different weight loss regimens, but specific trends indicate the merit of further exploration in larger datasets.

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## Assessing kidney disease risk in clinically obese youth: BMI better predicts renal tubular dysfunction, whilst BMI *z*-score better predicts glomerular filtration abnormalities

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**Background:** Obesity is a well-established risk factor for the development of renal disease in adults. In children the contribution of obesity to renal dysfunction is less well understood. We investigated the prevalence of renal dysfunction in an obese paediatric cohort with the aim of understanding which anthropometric characteristics would be better indicators of risk in a clinical setting.

**Methods:** Patients were enrolled into the Childhood Overweight Biorepository of Australia (COBRA) study, from the multidisciplinary weight management service at the Royal Children's Hospital in Melbourne ($n = 297$, M 47%, mean BMI *z*-score 2.47, mean BMI $35.74 \pm 6.38$, mean age 11 years). Extensive clinical, pathology and biochemistry data were collected. Renal function was assessed by eGFR, urinary albumin to creatinine ratio (ACR), urinary cystatin C, osteopontin, β2 microglobulin and NGAL. Statistical modelling was used to assess each measurement against anthropometric data; BMI *z*-score, BMI and total body fat %.

**Results:** BMI, but not BMI *z*-score correlated with urinary Cystatin C/creatinine ratio ($r = 0.249$, $p = 0.039$), urinary osteopontin ($r = 0.362$, $p = 0.005$) systolic ($r = 0.489$, $p < 0.001$) and diastolic blood pressure ($r = 0.271$, $p = 0.36$). Calculations for glomerular filtration correlated with BMI *z*-score (eGFR, $r = -0.409$, $p = 0.017$, ACR $r = 0.294$, $p = 0.017$). In multiple regression modelling age and BMI *z*-score accounted for 27% of the variation in eGFR ratio ($R = 0.572$, $p < 0.01$).

**Conclusion:** Paediatric obesity is a risk factor for the development of renal disease, and hence should be included in the common assessments of co-morbidities. Total BMI rather than BMI *z*-scores may better predict early renal disease.

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## Standardised baseline data collections in obesity management services in Australia: Recommendations from an expert panel

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**Background:** Specialist obesity management services that provide care by multi-disciplinary teams incorporating behavioural weight loss management programs, treatment with pharmacotherapy and bariatric surgery are an important, but currently limited, component of comprehensive obesity care in Australia [1]. At present, there is little collaboration or co-ordination across services that differ in composition and service provision. To address this issue, we aimed to develop an expert consensus on standardising data collection in specialist obesity services.

**Methods:** A panel of sixteen experts recruited from obesity management services in Australia participated in a structured consensus-driven Delphi process [2] to develop an agreed set of data that should be collected from patients during their initial attendance at specialist obesity services. The panel included surgeons, clinicians, allied health professionals (dietitian, exercise physiologist, psychologist), a bariatric nurse, and obesity researchers. We chose a 70% threshold to define attainment of consensus for data items to be included in the final baseline dataset.

**Results:** We produced a recommended list of core and useful data items that should comprise the initial patient dataset within obesity management services. Consensus was achieved for recommended measures of demographic, anthropometric, weight loss history, biochemical measures, medication, medical history and comorbidity data items and included consideration of data items specific to surgical patients. Measures of diet and physical activity were considered core but the best instruments for capturing such data could not be resolved in this study.

**Conclusion:** We present the first expert panel consensus on recommendations for standardised baseline patient data collection in obesity management services in Australia. Standardising data collections will minimise variation in clinical assessment and facilitate data pooling for clinical audit, health service planning, as well as future research activities.

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### Low copy number of the salivary amylase gene (AMY1) are associated with obesity, dyslipidemia and chronic low-grade inflammation but not insulin sensitivity and secretion

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Low salivary amylase gene (AMY1) copy number variations (CNVs)are associated with low serum amylase concentrations which have been shown to correlate with obesity, metabolic syndrome and predict type 2 diabetes. Recently, AMY1 CNV below 4 has been associated higher risk of obesity. Only one study has shown an association between AMY1 CNV and insulin resistance (HOMA).

We assessed the relationship between AMY1 CNVs and adiposity (body mass index and dual X-ray absorptiometry), fasting and 2 hour glucose (75 g OGTT), insulin sensitivity (hyperinsulinemic euglycemic clamp) and total, first and second phase insulin secretion (intravenous glucose tolerance test), inflammatory markers and adipokines (multiplex assays, Biolegend, CA) in 58 overweight and obese but otherwise healthy individuals (age $31 \pm 9$ years, BMI $31 \pm 4$ kg/m$^2$). Participants were non-smokers and had modest alcohol consumption. The participants were divided into two groups according to a median of 4 AMY1 CNVs.

Individuals with less than 4 AMY1 CNVs had higher BMI ($33 \pm 4$ vs $30 \pm 3$ kg/m$^2$, $p = 0.04$), fat mass ($41 \pm 12$ vs $34 \pm 8$ kg, $p = 0.01$), LDL cholesterol ($3.3 \pm 0.8$ vs $2.8 \pm 0.7$mmol/l, $p = 0.02$), plasma interleukin 6 ($53 \pm 56$ vs $24 \pm 22$ pg/ml, $p = 0.02$) and leptin concentrations ($0.83 \pm 0.56$ vs $0.50 \pm 0.46$ ng/ml, $p = 0.02$) compared to individuals with more than 4 AMY1 CNVs. There was no relationship between AMY1 CNVs and insulin sensitivity, insulin secretion, plasma fasting and 2 hour glucose, high sensitivity C-reactive protein, adiponectin, resistin and adipsin levels (all $p > 0.1$).

Our data indicated that AMY1 CNVs are associated with obesity, dyslipidemia and chronic low-grade inflammation but not glucose metabolism. Further larger studies are needed to confirm whether AMY1 CNVs could be a genetic biomarker for metabolic syndrome and type 2 diabetes.

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### Hypothalamic hunger promoting neurons drive life

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### Novel circulating biomarkers identify insulin resistance phenotypes in obesity

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**Objective:** Measurement of insulin resistance may ultimately assist in guiding the most effective therapy in type 2 diabetes (T2D). We aimed to identify circulating biomarkers of muscle and liver insulin resistance in obesity to guide treatment in the clinical setting.

**Research design and methods:** Metabolomics and lipidomics were combined with a specialized machine-learning algorithm to identify plasma biomarkers that characterize muscle and liver insulin resistance in a cohort of 62 individuals with obesity (BMI range 31â‰“48 kg/m$^2$) phenotyped using the gold-standard 2-step hyperinsulinaemic-euglycaemic clamp with deuterated glucose to evaluate glucose regulation in muscle and liver.

**Results:** Comprehensive metabolomic and lipidomic profiling by LC/MS revealed that a total of fourteen circulating metabolites and lipids were closely correlated with muscle insulin resistance (Spearman $rho > 0.2$, $p < 0.05$) while nineteen were associated with hepatic insulin resistance (Spearman $rho > 0.3$, $p < 0.05$). A hybrid learning model that combines clustering-based prototype selection and random forest-based feature analysis identified two triacylglycerols (TAGs) and a phosphatidylcholine (PC) in plasma as the best classifiers differentiating between the liver and muscle insulin resistance phenotypes, followed by select metabolites, clinical features, and biochemical parameters. The three lipids identified by the hybrid learning model far out-performed standard clinical

[9] O'Sullivan and Samocha-Bonet contributed equally to this work.