Transcripts with high distal heritability mediate genetic effects on complex traits

## Abstract

The transcriptome is increasingly viewed as a bridge between genetic risk factors for complex disease and their associated pathophysiology. Powerful insights into disease mechanism can be made by linking genetic variants affecting gene expression (expression quantiatitive trait loci - eQTLs) to phenotypes.

## Introduction

In the quest to understand the genetic architecture of complex traits, gene expression is an important bridge between genotype and phenotype. By identifying mediating transcripts, we get one step closer to a molecular understanding of how genetic variants influence traits. Moreover, there is evidence from genome-wide association studies (GWAS) that regulation of gene expression accounts for the bulk of the genetic effect on complex traits, as most trait-associated variants lie in gene regulatory regions1–7. It is widely assumed that these variants influence local transcription, and methods such as transcriptome-wide association studies (TWAS)8–11, summary data-based Mendelian randomization (SMR)10, and others have capitalized on this idea to identify genes associated with multiple disease traits12–15

Despite the great promise of these methods, however, they have not been as widely successful as it seemed they could have been, and the vast majority of complex trait heritability remains unexplained. Although trait-associated variants tend to lie in non-coding, regulatory regions, they often do not have detectable effects on gene expression16 and tend not to co-localize with expression quantitative trait loci (eQTLs)17,18.

One possible explanation for these observations is that gene expression is not being measured in the appropriate cell types and thus true eQTLs influencing traits cannot be detected16. An alternative explanation that has been discussed in recent years is that effects of these variants are mediated not through local regulation of gene expression, but through distal regulation15,18–20.

However, assessing the role of wide-spread distal gene regulation on complex traits requires large, dedicated data sets that include high-dimensional, clinically relevant phenotyping, dense genotyping in a highly recombined population, and transcriptome-wide measurements of gene expression in multiple tissues. Measuring gene expression in multiple tissues is critical to adequately assess the extent to which local gene regulation varies across multiple tissues and whether such variablilty might account for previous failed attempts to identify trait-relevant local eQTL. Such data sets are extremely difficult to obtain in human populations, particularly in the large numbers of subjects required for statistical testing. Thus, to investigate further the role of local and distal gene regulation on complex traits, we have generated an appropriate data set in a large population of diversity outbred (DO) mice21 in a population model of diet-induced obesity and metabolic disease12.

The DO mice were derived from eight inbred founder mouse strains, five classical lab strains, and three strains more recently derived from wild mice21. They represent three subspecies of mouse *Mus musculus domesticus*, *Mus musculus musculus*, and *Mus musculus casteneus*, and capture 90% of the known variation in laboratory mice [cite]. They are maintained with a breeding scheme that ensures equal contributions from each founder across the genome thus rendering almost the whole genome visible to genetic inquiry21. We measured clinically relevant metabolic traits, including body weight, plasma levels of insulin and glucose, and plasma lipids in 500 DO mice. We further measured transcriptome-wide gene expression in four tissues related to metabolic disease: adipose tissue, pancreatic islets, liver, and skeletal muscle.

To assess the role of gene regulation in mediating variation in metabolic traits in this population, we propose high-dimensional mediation (HDM). In univariate approaches, such as TWAS, SMR, and other Mendelian randomization approaches, each transcript is tested independently for mediation of a local variant on a trait. This process requires huge numbers of statistical tests, which is compuatationally expensive, requires strict corrections for multiple testing, and assumes independence of genetic variants and transcripts. Such methods are therefore limited to detecting only the largest statistical effects and are biased toward local gene regulation. In contrast, with high-dimensional mediation we assessed broad relationships among the genome, transcriptome, and phenome as a whole and identified a highly heritable composite trait that was perfectly mediated by a composite transcript. We show that composite transcripts were tissue-specific and highly interpretable in terms of biological processes as well as cell type composition. Heritability analysis of the transcripts showed that the strongest transcriptional mediators of metabolic disease had low local heritability and high distal heritability. Finally, we show that the composite transcripts identified in the DO population predicted obesity in an independent population of Collaborative Cross recombinant inbred (CC-RIX) mice and in human subjects. In contrast, local eQTL were unable to predict obesity in the CC-RIX mice. Together our results suggest that both the tissue used for gene expression analysis as well as distal gene regulation are critically important in identifying transcriptional mediators of the genome on complex traits.

## Results

### Genetic variation contributed to wide phenotypic variation

Although the environment was consistent across all animals, the genetic diversity present in this population resulted in widely varying distributions across physiological measurements (Fig. [1](#fig:trait_overview)). For example, body weights of adult individuals varied from less than the average adult B6 body weight to several times the body weight of a B6 adult in both sexes (Fig. [1](#fig:trait_overview)A). Fasting blood glucose (FBG) also varied considerably (Fig. [1](#fig:trait_overview)B) although few of the animals had FBG levels that would indicate pre-diabetes ( animals, ), or diabetes (7 animals, 1.4) according to previously developed cutoffs (pre-diabetes: FBG 250 mg/dL, diabetes: FBG 300, mg/dL)22. Males had higher FBG than females on average (Fig. [1](#fig:trait_overview)C) as has been observed before suggesting either that males were more susceptible to metabolic disease on the high-fat diet, or that males and females may require different thresholds for pre-diabetes and diabetes.

Body weight was strongly positively correlated with food consumption (Fig. [1](#fig:trait_overview)D 0.51, ) and fasting blood glucose (FBG) (Fig. [1](#fig:trait_overview)E, 0.21, ) suggesting a link between behavioral factors and metabolic disease. However, the heritability of this trait and others (Fig. [1](#fig:trait_overview)F) indicates that background genetics contribute substantially to correlates of metabolic disease in this population.

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Clinical overview. **A.** Distributions of final body weight in the diversity outbred mice. Sex is indicated by color. The average B6 male and female adult weights at 24 weeks of age are indicated by blue and green bars on the x-axis. **B.** The distribution of final fasting glucose across the population split by sex. Normal, pre-diabetic, and diabetic fasting glucose levels for mice are shown by colored bars along the x-axis. **C.** Males had higher fasting blood glucose on average than females. **D.** The relationship between food consumption and body weight for both sexes. **E.** Relationship between body weight and fasting glucose for both sexes. **F.** Heritability estimates for each physiological trait. Bars show standard error of the estimate. **G.** Correlation structure between pairs of physiological traits.

The landscape of trait correlations (Fig. [1](#fig:trait_overview)G) shows that most of the metabolic trait pairs were relatively weakly correlated indicating complex relationships among the measured traits. This low level of redundancy suggests a broad sampling of multiple heritable aspects of metabolic disease including overall body weight, glucose homeostasis, pancreatic composition and liver function.

### Distal Heritability Correlated with Phenotype Relevance

We performed eQTL analysis using R/qtl223 (Methods) and identified both local and distal eQTL for transcripts in each of the four tissues (Supp. Fig [9](#fig:eQTL)). Significant local eQTLs far outnumbered distal eQTLs (Supp. Fig. [9](#fig:eQTL)F) and tended to be shared across tissues (Supp. Fig. [9](#fig:eQTL)G) whereas the few significant distal eQTL we identified tended to be tissue-specific (Supp. Fig. [9](#fig:eQTL)H)

We calculated the heritability of each transcript in terms of local and distal genetic factors (Methods). Overall, local and distal genetic factors contributed approximately equally to transcript abundance. In all tissues, both local and distal factors explained between 8 and 18% of the variance in the median transcript (Fig [2](#fig:motivation)A).

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Transcript heritability and trait relevance. **A.** Distributions of distal and local heritability of transcripts across the four tissues. Overall local and distal factors contribute equally to transcript heritability. The relationship between (**B.**) local and (**C.**) distal heritability and trait relevance across all four tissues. Here trait relevance is defined as the maximum correlation between the transcript and all traits. Local heritability was negatively correlated with trait relevance, and distal heritability is positively correlated with trait relevance. Pearson () and values for each correlation are shown in the upper-right of each panel.

Local heritability of transcripts was negatively correlated with their trait relevance, defined as the maximum correlation of a transcript across all traits (Fig. [2](#fig:motivation)B). This suggests that the more local genotype influenced transcript abundance, the less effect variation in transcript abundance had on the measured traits. Conversely, distal heritability of transcripts was positively correlated with trait relevance (Fig. [2](#fig:motivation)C). That is, transcripts that were more highly correlated with the measured traits tended to be distally, rather than locally, heritable. That trait-correlated transcripts have low local heritability is consistent with previous observations that low-heritability transcripts explain more expression-mediated disease heritability than high-heritability transcripts19. However, the positive relationship between trait correlation and distal heritability suggests that there are alternative mechanisms through which genetic regulation of transcripts may influence traits.

### High-Dimensional Mediation identified a high-heritability composite trait that was perfectly mediated by a composite transcript

We used high-dimensional mediation to identify the major axis of variation in the transcriptome that mediated the effects of the genome on metabolic traits (Fig. [3](#fig:workflow)). We kernelized the genome, phenome, and transcriptome matrices and used generalized canonical correlation analysis (RGCCA)24 to identify a composite transcript () that perfectly mediated the effect of the composite genome () on the composite phenome ().

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High-dimensional mediation. **A.** Workflow indicating major steps of high-dimensional mediation. The genotype, transcriptome, and phenotype matrices were kernelized to yield single matrices representing the relationships between all individuals for each data modality ( = genome kernel, = transcriptome kernel; = phenome kernel). High-dimensional mediation was applied to these matrices to maximize the direct path , the mediating pathway (arrows), while simultaneously minimizing the direct pathway (dotted line). The composite vectors that resulted from high-dimensional mediation were , , and . The partial correlations between these vectors indicated perfect mediation. Transcript and trait loadings were calculated as described in the methods. **B.** The null distribution of the path coefficient derived from 10,000 permutations compared to the observed path coefficient (red line). **C.** The null distribution of the - correlation vs. the - correlation compared with the observed value (red dot).

Fig. [3](#fig:workflow)A shows the partial correlations () between the pairs of these composite vectors. The partial correlation between and was 0.42, and the partial correlation between and was 0.78. However, when the transcriptome was taken into account, the partial correlation between and was effectively 0 (0.039). The estimated heritability of the composite phenome was heritability of 0.71 0.084, which was higher than any of the individual traits (Fig. [1](#fig:trait_overview)F). Thus, we have identified a maximally heritable metabolic trait that is perfectly mediated by a heritable component of the transcriptome.

Standard CCA is prone to over-fitting because in any two large matrices it can be trivial to identify highly correlated composite vectors. To assess whether RGCCA was similarly prone to over-fitting in a high-dimensional space, we performed permutation testing. We permuted the individual labels on the transcriptome kernel matrix 1000 times and recalculated the path coefficient, which is the partial correlation of and multiplied by the partial correlation of and . This represents the path from to that is mediated through . The null distribution of the path coefficient is shown in Fig. [3](#fig:workflow)B, and the observed path coefficient from the original data is indicated by the red line. The observed path coefficient was well outside the null distribution generated by permutations. Fig. [3](#fig:workflow)C illustrates this observation in more detail. Although we identified high correlations between and , and modest correlations between and in the null data (Fig [3](#fig:workflow)C), these two values could not be maximized simultaneously. The red dot shows that in the real data both the - correlation and the - correlation could be maximized simultaneously suggesting that the path from genotype to phenotype through transcriptome is highly non-trivial and identifiable in this case. These results suggest that these composite vectors represent genetically determined variation in phenotype that is mediated through genetically determined variation in transcription.

### Body weight and insulin resistance were highly represented in the expression-mediated composite trait

The loadings of each measured trait onto indicate how much each contributed to the composite phenotype. Final body weight contributed the most (Fig. [4](#fig:interpretation)), followed by homeostatic insulin resistance (HOMA\_IR) and fasting plasma insulin levels (Insulin\_Fasting). We can thus interpret as an index of metabolic disease (Fig. [4](#fig:interpretation)B). Individuals with high values of have a higher metabolic index and greater metabolic disease, including higher body weight and higher insulin resistance. We refer to as the metabolic index going forward. Traits contributing the least to the metabolic index were measures of cholesterol and pancreas composition. Thus, when we interpret the transcriptomic signature identified by HDM, we are explaining primarily transcriptional mediation of body weight and insulin resistance, as opposed to cholesterol measurements.

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Interpretation of loadings. **A.** Loadings across traits. Body weight and insulin resistance contributed the most to the composite trait. **B.** Phenotype scores across individuals. Individuals with large positive phenotype scores had higher body weight and insulin resistance than average. Individuals with large negative phenotype scores had lower body weight and insulin resistance than average. **C.** Distribution of transcript loadings in adipose tissue. For transcripts with large positive loadings, higher expression was associated with higher phenotype scores. For transcripts with large negative loadings, higher expression was associated with lower phenotype scores. **D.** Distribution of absolute value of transcript loadings across tissues. Transcripts in adipose tissue had the largest loadings indicating that transcripts in adipose tissue were the best mediators of the genetic effects on body weight and insulin resistance.

### High-loading transcripts have low local heritability, high distal heritability, and were linked mechanistically to obesity

We interpreted large loadings onto transcripts as indicating strong mediation of the effect of genetics on metabolic index. Large positive loadings indicate that higher expression was associated with a higher metabolic index (i.e. higher risk of obesity and metabolic disease on the high-fat diet) (Fig. [4](#fig:interpretation)C). Conversely, large negative loadings indicate that high expression of these transcripts was associated with a lower metabolic index (i.e. lower risk of obesity and metabolic disease on the high-fat diet) (Fig. [4](#fig:interpretation)C). We used gene set enrichment analysis (GSEA)25,26 to look for biological processes and pathways that were enriched at the top and bottom of this list (Methods).

In adipose tissue, both GO processes and KEGG pathway enrichments pointed to an axis of inflammation and metabolism (Supp. Fig. [10](#fig:top_enrich_kegg) and [11](#fig:top_enrich_go)). GP terms and KEGG pathways associated with inflammation, particularly macrophage infiltration, were positively associated with metabolic index, indicating that increased expression in inflammatory pathways was associated with a higher metabolic index. It is well established that adipose tissue in obese individuals is highly inflamed [cite] and infiltrated by macrophages [cite], and the results here suggest that this may be a heritable component of metabolic disease.

The strongest negative enrichments in adipose tissue were related to mitochondial activity in general, and thermogenesis in particular (Supp. Fig. [10](#fig:top_enrich_kegg) and [11](#fig:top_enrich_go)). It has been shown mouse strains with greater thermogenic potential are also less susceptible to obesity on a high-fat diet [cite].

Transcripts associated with the citric acid (TCA) cycle as well as the catabolism of branched-chain amino acids (BCAA), valine, leuceine, and isoleucine were strongly enriched with negative loadings in adipose tissue (Supp. Fig. XXX). Expression of genes in both pathways (for which there is some overlap) has been previously associated with insulin sensitivity12,27,28, suggesting that heritable variation in regulation of these pathways may influence risk of insulin resistance.

Looking a the 10 strongest positive and negative loaded transcripts from each tissue, is is apparent that transcripts in the adipose tissue had the largest loadings, both positive and negative, of all tissues (Fig. [5](#fig:loading_heritability)A bar plot) This suggesting that much of the effect of genetics on body weight and insulin reisistance is mediated through gene expression in adipose tissue. The strongest loadings in liver and pancreas were comparable, and those in skeletal muscle were the weakest (Fig. [5](#fig:loading_heritability)A), suggesting that less of the genetic effects were mediated through transcription in skeletal muscle. Heritability analysis showed that trahscripts with the largest loadings tended to have relatively high distal heritability compared with local heritability (Fig. [5](#fig:loading_heritability)A heat map and box plot). This pattern contrasts with transcripts nominated by TWAS (Fig. [5](#fig:loading_heritability)B), which tended to have lower loadings, higher local heritability and lower distal heritability. Transcripts with the highest local heritability in each tissue (Fig. [5](#fig:loading_heritability)C) had the lowest loadings.

We performed a literature search for the genes in each of these groups along with the terms “diabetes”, “obesity”, and the name of the expressing tissue to determine whether any of these genes had previous associations with metabolic disease in the literature (Methods). Multiple genes in each group had been previously associated with obesity and diabetes (Fig. [5](#fig:loading_heritability) bolded gene names). Genes with high loadings were most highly enriched for previous literature support. They were 2.25 more likely than TWAS hits and 3.6 times more likely than genes with high local heritability to be previously associated with obesity or diabetes.

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Transcripts with high loadings have high distal heritability and literature support. Each panel has a bar plot showing the loadings of transcripts selected by different criteria. Bar color indicates the tissue of origin. The heat map shows the local (L - left) and distal (D - right) heritability of each transcript. **A.** Loadings for the 10 transcripts with the largest positive loadings and the 10 transcripts with the largest negative loadings for each tissue. **B.** Loadings of TWAS candidates with the 10 largest positive correlations with traits and the largest negative correlations with traits across all four tissues. **C.** The transcripts with the largest local heritability (top 20) across all four tissues.

### Tissue-specific transriptional programs were associated with metabolic traits

Clustering of transcripts with top loadings in each tissue showed tissue-specific functional modules associated with obesity and insulin resistance (Fig. [6](#fig:toa)A) (Methods). The clustering highlights the importance of immune activation particularly in adipose tissue. Except fo the “mitosis” cluster, which had large positive loadings in three of the four tissues, all clusters were strongly loaded in only one or two tissues. For example, the lipid metabolism cluster was loaded most heavily in liver. The positive loadings suggest that high expression of these genes particualarly in the liver was associated with increased metabolic disease. This cluster included the gene *Pparg*, whose primary role is in the adipose tissue where it is considered a master regulator of adipogenesis29. Agonists of *Pparg*, such as Thiazolidinediones, which are FDA-approved to treat type II diabetes, reduce inflammation and adipose hyptertrophy29. Consistent with this role, the loading for *Pparg* in adipose tissue was negative, suggesting that higher expression was associated with leaner mice (Fig. [6](#fig:toa)B). In contrast, *Pparg* had a large positive loading in liver, where it is known to play a role in the development of hepatic steatosis, or fatty liver. Mice that lack *Pparg* specifically in the liver, are protected from developing steatosis and show reduced expression of lipogenic genes30,31. Overexpression of *Pparg* in the livers of mice with a *Ppara* knockout, causes upregulation of genes involved in adipogenesis32. In the livers of both mice and humans high *Pparg* expression is associated with hepatocytes that accumulate large lipid droplets and have gene expression profiles similar to adipocytes33,34.

The local and distal heritability of *Pparg* is low in adipose tissue suggesting its expression in this tissue is highly constrained in the population (Fig. [6](#fig:toa)B). However, the distal heritability of *Pparg* in liver is relatively high suggesting it is complexly regulated and has sufficient variation in this population to drive variation in phenotype. Both local and distal heribatility of *Pparg* in the islet are fairly high, but the loading is low, suggesting that variability of expression in the islet does not drive phenotypic variation. These results highlight the importance of tissue context when investigating the role of heritable transcript variability in driving phenotype.

Gene lists for all clusters are available in Supplemental File XXX.

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Tissue-specific transcriptional programs were associated with obesity and insulin resistance. **A** Heat map showing the loadings of all transcripts with loadings greater than 2.5 standard deviations from the mean in any tissue. The heat map was clustered using k medoid clustering. Functional enrichments of each cluster are indicated along the left margin. **B** Loadings for *Pparg* in different tissues. **C** Local and distal of *Pparg* expression in different tissues.

### Gene expression, but not local eQTLs, predicted body weight in an independent population

To test whether the transcript loadings identified in the DO could be translated to another population, we tested whether they could predict metaoblic a phenotype in an independent population of CC-RIX mice, which were F1 mice derived from multiple pairings of Collaborative Cross (CC) [cite] strains (Fig. [7](#fig:cc_prediction)) (Methods). We tested two questions. First, we asked whether the loadings identified in the DO mice were relevant to the relationship between the transcriptome and the phenome in the CC-RIX. We predicted body weight in each CC-RIX individual using measured gene expression in each tissue and the transcript loadings identified in the DO (Methods). The predicted body weight and acutal body weight were highly correlated in all tissues (Fig. [7](#fig:cc_prediction)B left column). The best prediction was achieved for adipose tissue, which supports the observation in the DO that adipose expression was the strongest mediator of the genetic effect on metabolic index. This result also confirms the validity and translatability of the transcript loadings and their relationship to metabolic disease.

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Transcription, but not local genotype, predicts phenotype in the CC-RIX. **A.** Workflow showing procedure for translating HDM results to an independent population of mice. **B.** Relationships between the predicted metabolic index and measured body weight. The left column shows the predictions using measured transcripts. The right column shows the prediction using transcript levels imputed from local genotype. Gray boxes indicate measured quantities, and blue boxes indicate calculated quantities. The dots in each panel represent individual CC-RIX strains. The gray lines show the standard deviation on body weight for the strain.

The second question related to the source of the relevant variation in gene expression. If local regulation was the predominant factor influencing gene expression, we should be able to predict phenotype in the CC-RIX using transcripts imputed from local genotype (Fig. [7](#fig:cc_prediction)A). The DO and the CC-RIX were derived from the same eight founder strains and so carry the same alleles throughout the genome. We imputed gene expression in the CC-RIX using local genotype and were able to estimate variation in gene transcription robustly (Supp. Fig. [12](#fig:cc_imputation)). However, these imputed values failed to predict body weight in the CC-RIX when weighted with the loadings from HDM. (Fig. [7](#fig:cc_prediction)B right column). This result suggests that local regulation of gene expression is not the primary factor driving heritability of complex traits.

### Distally heritable transcriptomic signatures reflected variation in composition of adipose tissue and islets

Interpretation of global genetic influences on gene expression and phenotype is potentially more challenging than interpretation and translation of local genetic influences, as genetic effects cannot be localized to individual gene variants or transcripts. However, there are global patterns across the loadings that can inform mechanism. For example, heritable variation in cell type composition can be derived from transcript loadings. We noted earlier that immune activation in the adipose tissues was an important driver of obesity in the DO population. To determine whether this is reflected as an increase in macrophages in adipose tissue, we compared loadings of cell-type specific genes in adipose tissue (Methods). The mean loading of macrophage-specific genes was substantially greater than 0 (Fig. [8](#fig:human_translation)A), indicating that obese mice were genetically predisposed to have high levels of macrophage infiltration in adipose tissue in response to the high-fat, high-sugar diet.

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HDM results translate to humans. **A.** Distribution of loadings for cell-type-specific transcripts in adipose tissue. **B.** Distribution of loadings for cell-type-specific transcripts in pancreatic islets (green). **C.** Null distributions for the mean loading of randomly selected transcripts in each cell type compared with the observed mean loading of each group of transcripts (red asterisk). **D.** Predictions of metabolic phenotypes in four adipose transcription data sets downloaded from GEO. In each study the obese/diabetic patients were predicted to have greater metabolic disease than the lean/non-diabetic patients based on the HDM results from DO mice.

We also compared loadings of cell-type specific transcripts in islet (Methods). The mean loadings for alpha-cell specific transcripts were significantly greater than 0, while the mean loadings for delta- and endothelial-cell specific genes were significantly less than 0 (Fig. [8](#fig:human_translation)B). These results suggest that obese mice had inherited higher proportions of alpha cells, and lower proportions of endothelial and delta cells in their pancreatic islets.

The loadings for pancreatic beta cell-type specific loadings was not significantly different from zero. This is not necessarily reflective of the function of the beta cells in the obese mice, but rather suggests that any variation in the number of beta cells in these mice was unrelated to obesity and insulin resistance.

### Heritable transcriptomic signatures translated to human disease

Ultimately, the heritable transcriptomic signatures that we identified in DO mice will be useful if they inform pathogenicity and treatment of human disease. To investigate the potential for translation of the gene signatures identified in DO mice, we compared them to transcriptional profiles in obese and non-obese human subjects (Methods). We limited our analysis to adipose tissue because the adipose tissue signature had the strongest relationship to obesity and insulin resistance in the DO.

We calculated a predicted obesity score for each individual in the human studies based on their adipose tissue gene expression (Methods) and compared the predicted scores for obese and non-obese groups as well as diabetic and non-diabetic groups. In all cases, the predicted obesity scores were higher on average for individuals in the obese and diabetic groups compared with the lean and non-diabetic groups (Fig. [8](#fig:human_translation)D). This indicates that the heritable signature of obesity identified in DO mice is relevant to obesity and diabetes in human subjects.

### Targeting gene signatures

Another global view of the transcript loading landscape is in ranking potential drug candidates for the treatment of metabolic disease. Although high-loading transcripts may be good candidates for understanding specific biology related to obesity, the transcriptome overall is highly interconnected and redundant, and focusing on individual transcripts for treatment may be less effective than using a broader transcriptomic signatures. The ConnectivityMap (CMAP) database [cite] developed by the Broad Institute allows us to query thousands of compounds that reverse or enhance the extreme ends of transcriptomic signatures in multiple different cell types. By identifying drugs that reverse pathogenic transcriptomic signatures, we can potentially identify compounds that have favorable effects on gene expression.

To test this hypothesis we queried the CMAP database through the CLUE online query tool [cite] (Methods). We identified top anti-correlated hits both across all cell types, as well as in adipocytes and pancreatic tumor cells (Supplemental Figure XXX and XXX).

Looking broadly across cell types, the notable top hits from the adipose tissue loadings included mTOR inhibitors and glucocorticoid agonists (Supplemental Figure XXX). It is thought that metformin, which is commonly used to improve glycemic control, acts, at least in part, by inhibiting mTOR signaling35,36. However, long-term use of other mTOR inhibitors, such as rapamycin, are known to cause insulin resistance and -cell toxicity36–38. Glucocorticoids are used to reduce inflammation, which was a prominent siganture in the adipose tissues, but these drugs also promote hyperglycemia and diabetes39,40. Accute treatment with glucocorticoids has further been shown to reduce thermogenesis in rodent adipocytes41–43, but increase thermogenesis in human adipocytes44,45. Thus, the pathways identified by CMAP across all cell types were highly related to the transcript loading profiles, but the relationship was not a simple reversal.

The top hit in adipocytes was a PARP inhibitor (Supplemental Figure XXXB). PARPs play a role in lipid metabolism and are involved in the development of obesity and diabetes46. PARP1 inhibition increases mitochondrial biogenesis47. Inihibition of PARP1 activity can further prevent necrosis in favor of the less inflammatory apoptosis48, thereby potentially reducing inflammation in stressed adipocytes. Other notable hits in the top 20 were BTK inhibitors, which have been observed to suppress inflammation and improve insulin resistance49 as well as to reduce insulin antibodies in type I diabetes50. Similarly, IKK has been shown to be associated with insulin resistance51, and inhibitors have been shown to improve glucose control in type II diabetes52.

Among the top hits for the query with transcript loadings from pancreatic islets (Fig. XXX), was suppression of T cell receptor signaling, which is known to be involved in Type 1 diabetes53, as well as TNFR1, which has been associated with mortality in diabetes patients54. Suppression of NOD1/2 signaling was also among the top hits. NOD1 and 2 sense ER stress55,56, which is associated with -cell death in type 1 and type 2 diabetes57. This cell death process is dependent on NOD1/2 signaling55, although the specifics have not yet been worked out.

Among the top hits in pancreatic tumor cells were known diabetes drugs, including sulfonylureas, PPAR receptor agonists, and insulin sensitizers. Rosiglitazone is a PPAR- agonist and was one of the most prescribed drugs for type 2 diabetes before its use was reduced due to cardiac side-effects58. Sulfonylureas are another commonly prescribed drug class for type 2 diabetes, but also have notable side effects including hypoglycemia and accellerated -cell death59.

## Discussion

It is thought that the bulk of the effect of genomic variation on complex traits is mediated through regulation of gene expression. It has widely been assumed that this regulation is largely in *cis*, but attempts to use local gene regulation to explain phenotypic variation have yet to explain much trait heritability. In recent years, the discussion has turned to distal gene regulation. Although, distal gene regulation is more complex to identify, evidence suggests that it is an important component of trait heritability.

Yao *et al.*19 observed that in humans, transcripts with low local heritability explained more expression-mediated disease heritability than transcripts with high local heritability. We observed the same trend here in mice. This pattern is consistent with principles of robustness in complex systems60–62. If a transcript were both important to a trait and subject to strong local regulation, a population would be susceptible to extremes in phenotype that might frequently cross the threshold to disease. Indeed, strong disruption of highly trait-relevant genes is the cause of Mendelian disease.

Rather, studies suggest that genes that are near GWAS hits and have obvious functional relevance to a trait tend to have highly complex regulatory landscapes under strong selection pressures18. In contrast, genes with strong local regulation tend to be depleted of functional annotations and are under looser selection constraints18. These observations and others led Liu et al. 63 to suggest that most heritability of complex traits is driven by weak distal eQTLs. They proposed a framework of understanding heritability of complex traits in which massive polygenicity is distributed across common variants in both functional “core genes”, as well as more peripheral genes that may not seem obviously related to the trait.

Here, we used a large, comprehensive, and purpose-built data set to investigate the genetic architecture of complex traits related to metabolic disease in mice as well as the roles of local and distal gene regulation in mediating these traits. We presented a systems-level method called high-dimension mediation (HDM). This approach contrasts with traditional univariate approaches in several important respects. First, in contrast to univariate approaches, which assume independence of genetic variants and transcripts, HDM allows for arbitrarily complex gene regulation, as well as the interconnectedness and redundancy of the transcriptome. Second, rather than assuming a single, large genetic effect as univariate approaches do, HDM assumes that traits are highly polygenic, and that genetic effects are weak and are distributed across the genome. HDM does not use statistical threholds to identify true positive effects, but generates a weighted vector of transcripts that can be analyzed as a whole, or dissected to identify transcripts with stronger and weaker effects. This method explicitly models a central proposal of the omnigenic model which posits that once the expression of the core genes (i.e.  trait-mediating genes) is accounted for, there should be no residual correlation between the genome and the phenome.

Using HDM, we identified a highly heritable comopsite trait (71% heritable) that was perfectly mediated by a composite transcript that included expression from four tissues known to be involved in metabolic disease. Gene expression in adipose tissue was the strongest mediator of genetic effects on metabolic disease. Further analysis of the loadings onto transcripts in each tissue revealed that the mediating signatures were tissue-specific transcriptional programs, many of which were previously known to be involved in the pathogenesis of metabolic disease. We showed here that regulation of these programs is heritable and mediated a large proportion of disease risk.

The transcripts with the highest loadings are similar to the core genes of the omnigenic model. These were transcripts of moderate heritability that were highly functionally related to the traits. Transcripts with small loadings are more peripheral to the traits measured in this experiment. There was no clear demarcation between the core and peripheral genes as far as loading, but a clear separation should not be expected given the complexity of gene regulation and the genotype-phenotype map.

The strength of mediation (transcript loading) was negatively correlated with local heritability and positively correlated with distal heritability, suggesting that distal gene regulation was the dominant mode through which gene expression mediated the effect of genotype on phenotype. We saw further that the distal heritability was weak and spread across the genome, consistent with the prediction by Liu *et al.*63 that trait heritability is mediated through weak distal eQTLs. Most strongly mediating transcripts had modest distal heritability, and even for those whose expression was strongly regulated by distal factors, these factors were multiple and spread across the genome. For example, , was a strongly mediating transcript in islet and was also strongly distally regulated (66% distal heritability). This gene is expressed in pancreatic cells and is involved in insulin and glucagon release64–66. Although its transcription was highly heritable in islets, that regulation was distributed across the genome, with no clear distal eQTL (Supp. Fig. [13](#fig:Nucb2_eqtl)). Thus, although distal regulation of some genes may be strong, this regulation is likely to be highly complex and not easily localized.

The high complexity of gene regulation combined with a systems-level analysis yields continuous results that do not necessarily implicate individual transcripts or genetic loci in disease pathogenesis. Most studies have focused on pinpointing individual loci whose mechanistic roles can be clearly dissected through further experiments. In this analysis, too, it is possible to focus on individual genes and their context in both tissues and pathways. For example, we showed that the loadings on *Pparg* were tissue-specific in a way that comports with known biology, i.e. it is known to be protective in adipose tissue where it was negatively loaded, and harmful in the liver, where it was positively loaded. However, continuous results can also be quite informative in their own right. Combined with increasing amounts of high-dimensional data in public databases, weighted vectors can be useful for generating hypotheses and potential drug treatments. We showed that weighted vectors of genes can be analyzed for enriched biological functions and pathways using GSEA. These vectors can also be paired with data about cell-type specific genes to generate hypotheses about cell composition in individual tissues. Gene expression derived from patient biopsies confirmed that the transcriptional signatures we identified in mice predict obesity status in humans, further supporting the translatability of these results. Finally, we used the CMAP database to show that the transcriptomic signatures we identified in mice could be translated into human drug targets, as currently used diabetes drugs were among the top hits for reversing the disease-associated signatures. That these drugs are known to reverse diabetes pathogenesis supports the causal role of these gene signatures in disease risk as modeled by high-dimensional mediation.

In conclusion, we have shown that both tissue specificity and distal gene regulation are critically important to understanding the genetic architecture of complex traits. Although our systems approach does not identify individal genetic loci conferring risk of metabolic disease, we identified important genes and gene signatures that were heritable, causal of disease, and translatable to other mouse populations and to humans. Finally, we have shown that by directly acknowledging the complexity of both gene regulation and the genotype-to-phenotype map, we can gain a new perspective on disease pathogenesis and develop actionable hypotheses about pathogenic mechanisms and potential treatments.

## Data Availability

Here we tell people where to find the data

## Acknowledgements

Here we thank people

## Supplemental Figures

![](data:application/pdf;base64,)

Overview of eQTL analysis in DO mice. **A.** RNA seq samples from the four different tissues clustered by tissue. **B.-E.** eQTL maps are shown for each tissue. The -axis shows the position of the mapped eQTL, and the -axis shows the physical position of the gene encoding each mapped transcript. Each dot represents an eQTL with a minimum LOD score of 8. The dots on the diagonal are locally regulated eQTL for which the mapped eQTL is at the within 4Mb of the encoding gene. Dots off the diagonal are distally regulated eQTL for which the mapped eQTL is distant from the gene encoding the transcript. **F.** Comparison of the total number of local and distal eQTL with a minimum LOD score of 8 in each tissue. All tissues have comparable numbers of eQTL. Local eQTL are much more numerous than distal eQTL. **G.** Counts of transcripts with local eQTL shared across multiple tissues. The majority of local eQTL were shared across all four tissues. **H.** Counts of transcripts with distal eQTL shared across multiple tissues. The majority of distal eQTL were tissue-specific and not shared across multiple tissues. For both G and H, eQTL for a given transcript were considered shared in two tissues if they were within 4Mb of each other. Colored bars indicate the counts for individual tissues for easy of visualization.

![](data:application/pdf;base64,)

Bar plots showing normalized enrichment scores (NES) for KEGG pathways as determined by fast gene score enrichment analysis (fgsea). Only the top 10 positive and top 10 negative scores are shown. Colors indicate tissue. The name beside each bar shows the name of each enriched KEGG pathway.

![](data:application/pdf;base64,)

Bar plots showing normalized enrichment scores (NES) for GO terms as determined by fast gene score enrichment analysis (fgsea). Only the top 10 positive and top 10 negative scores are shown. Colors indicate tissue. The name beside each bar shows the name of each enriched GO term. The letters in parentheses indicate whether the term is from the biological process ontology (BP), the molecular function ontology (MF), or the cellular compartment ontology (CC).

![](data:application/pdf;base64,)

Validation of transcript imputation in the CC-RIX. **A.** Distributions of correlations between imputed and measured transcripts in the CC-RIX. The mean of each distribution is shown by the red line. All distributions were skewed toward positive correlations and had positive means near a Pearson correlation (r) of 0.5. **B.** The relationship between the correlation between measured and imputed expression in the CC-RIX (x-axis) and eQTL LOD score. As expected, imputations are more accurate for transcripts with strong local eQTL. **C.** Variance explained by local genotype in the DO and CC-RIX.

![](data:application/pdf;base64,)

Regulation of *Nucb2* expression in islet. *Nucb2* is encoded on mouse chromosome 7 at 116.5 Mb (red line). In islets the heritability of *Nucb2* expression levels is 69% heritable. This LOD score trace shows that there is no local eQTL at that position, nor any strong distal eQTL anywhere else in the genome.

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