# PHARMACOGENETICS OF SELECT GENES IN 

# THE OPIATE METABOLISM AND 

 RESPONSE PATHWAYS
## A DISSERTATION

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Frank R Wendt, B.S.

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## LIST OF ABBREVIATIONS

| ABCB1 | ATP binding cassette subfamily B number 1 |
| :--- | :--- |
| ACB | African Caribbeans in Barbados |
| ADME | Absorption, distribution, metabolism, excretion |
| ADME-R | Absorption, distribution, metabolism, excretion, and response |
| AFR | African |
| ALU | Arthrobacter luteus element |
| AMR | Admixed American |
| ANOVA | Analysis of variance |
| AS | Activity score |
| ASW | American of African Ancestry in Southwest United States |
| ATP | Adenosine triphosphate |
| bam | Batch alignment/map (file type) |
| BEB | Bengali from Bangladesh |
| BIC | Bayesian information criterion |
| BWA | Burrows-Wheeler Aligner |
| CADD | Combined Annotation Dependent Depletion |
| CCD | Charge-coupled device |
| CDX | Chinese Dai in Xishuangbanna, China |
| CEU | Utah Residents (CEPH) with Northern and Western Ancestry |
| CHB | Han Chinese in Beijing China |
| CHS | Southern Han Chinese |
| CLM | Colombians from Medellin, Colombia |
| CLP | Cleanup plate |
| CNV | Copy number variation |
| CoD | Cause of death |
| COMT | Catechol-O-methyltransferase |
| CYP2D6 | Cytochrome p450, family 2, subfamily D, polypeptide 6 |
| CYP2D7P | Cytochrome p450, family 2, subfamily D, polypeptide 7 pseudogene |
| CYP2D8P | Cytochrome p450, family 2, subfamily D, polypeptide 8 pseudogene |
| CYP450 | Cytochrome p450 mono-oxygenase |
| DI | Degradation index |
| DMSO | Dimethyl sulfoxide |
| DNA | Deoxyribonucleic acid |
| dNTP | Deoxynucleotide triphosphate |
| EAS | East Asian |
| EM | Extensive metabolizer |
| ESN | Esan in Nigeria |
|  |  |

## LIST OF ABBREVIATIONS (continued)

| EUR | European |
| :--- | :--- |
| EWAS | Exome-wide association study |
| FIN | Finnish in Finland |
| g-MP | Genotype-inferred metabolizer phenotype |
| GATK | Genome Analysis Toolkit |
| GCTA | Genome-wide Complex Trait Analysis |
| GBR | British in England and Scotland |
| GDA | Genetic Data Analysis |
| GenCall | Genotype call score |
| GIH | Gujarati Indian from Houston, Texas |
| GO | Gene ontology |
| GUSBP11 | Putative inactive beta-glucuronidase protein 11 |
| GWAS | Genome wide association study |
| GWD | Gambian in Western Divisions in Gambia |
| h $^{2}$ | Heritability |
| HCN1 | Potassium/sodium hyperpolarization-activated cyclic nucleotide-gated channel |
| HCYPAND | Human cytochrome p450 allele nomenclature database |
| He | Expected heterozygosity |
| Hg19 | Human genome build 19 |
| Hg38 | Human genome build 38 |
| Ho | Observed heterozygosity |
| HSF | Human Splicing Finder |
| HWE | Hardy-Weinberg equilibrium |
| HYP | Hybridization plate |
| IBD | Identity-by-descent |
| IBS | Iberian Population in Spain (Chapters 2-4); Identity-by-state (Chapter 7) |
| ICA1 | Islet cell autoantigen 1 |
| ICA69 | Islet cell autoantigen 1 |
| ICAp69 | Islet cell autoantigen 1 |
| ICD-10 | International Classification of Diseases, Tenth Revision |
| IGV | Integrated Genomics Viewer |
| IM | Intermediate metabolizer |
| INDEL | Insertion/deletion |
| IPC C | Internal PCR cycle threshold |
| ITU | Indian Telugu from the United Kingdom |
| JPT | Japanese in Tokyo, Japan |
| KHDRBS3 | KH domain-containing, RNA-binding, signal transduction-associated protein |
|  |  |

# LIST OF ABBREVIATIONS (continued) 

| KHV | Kinh in Ho Chi Minh City, Vietnam |
| :--- | :--- |
| LD | Linkage disequilibrium |
| LR | Linear regression classifier |
| LWK | Luhya in Webuye, Kenya |
| M6G | Morphine-6-glucuronide |
| M1 | O-desmethyltramadol |
| MAF | Minor allele frequency |
| MDR1 | Multidrug resistance protein 1 |
| MDS | Multidimensional scaling |
| miRNA | Micro RNA |
| MoD | Manner or death |
| MOR | Mu opioid receptor 1 |
| MP | Metabolizer phenotype |
| MPS | Massively parallel sequencing |
| MSL | Mende in Sierra Leone |
| MXL | Mexican Ancestry from Los Angeles, USA |
| 1NN | 1-nearest neighbor classifier |
| N | Nortramadol |
| NC | No genotype call |
| NM | Normal metabolizer |
| NM-F | Normal metabolizer, fast |
| NM-S | Normal metabolizer, slow |
| kNN | k-nearest neighbor classifier |
| OPR | Opioid receptor |
| OPRM1 | Opioid receptor mu 1 |
| p10 GC | Tenth percentile genotype call score |
| p50 GC | Fiftieth percentile genotype call score |
| PC1 | Principal component 1 |
| PC2 | Principal component 2 |
| PCA | Principal component analysis |
| PCR | Polymerase chain reaction |
| PEL | Peruvians from Lima, Peru |
| PGM | Personal Genome Machine |
| PharmGKB | Pharmacogenomics Knowledgebase |
| PharmVar | Pharmacogene Variation Consortium |
| PJL | Punjabi from Lahore, Pakistan |
| PM | Poor metabolizer |
|  |  |

## LIST OF ABBREVIATIONS (continued)

| PolyPhen-2 | Polymorphism Phenotyping v2 |
| :--- | :--- |
| PopART | Population Analysis with Reticulate Trees |
| PROVEAN | PROtein Variant Effect ANalyzer |
| PTC | Phenylthiocarbamide |
| PUR | Puerto Ricans from Puerto Rico |
| RF | Random forest classifier |
| RFL4B | Ret Finger Protein-like 4B |
| RGL4 | Ral Guanine Nucleotide Dissociation Stimulator Like 4 |
| RMLR | Regularized multinomial logistic regression |
| RNA | Ribonucleic acid |
| RNF211 | RING Finger Protein 211 |
| SALP | KH domain-containing, RNA-binding, signal transduction-associated protein |
| SAMtools | Sequence Alignment/Map Tools |
| SAS | South Asian |
| SIFT | Sort Intolerant From Tolerant |
| SLM2 | KH domain-containing, RNA-binding, signal transduction-associated protein |
| SMRT | Single molecular, real time sequencing |
| SNP | Single nucleotide polymorphism |
| SNV | Single nucleotide variant |
| STU | Sri Lankan Tamil from the United Kingdom |
| T | Tramadol |
| t-MP | Toxicologically-inferred metabolizer phenotype |
| TSCA | TruSeq Custom Amplicon |
| TSI | Toscani in Italia |
| T-STAR | KH domain-containing, RNA-binding, signal transduction-associated protein |
| UCSC | University of California Santa Cruz |
| UGT | Uridine diphosphate glucuronosyltransferase superfamily |
| UGT2B7 | Uridine diphosphate glucuronosyltransferase, family 1, polypeptide B7 |
| UM | Ultra-rapid metabolizer |
| UNTHSC | University of North Texas Health Science Center |
| vcf | Variant call format (file type) |
| WEKA | Waikato Enrvironment for Knowledge Analysis |
| WHO | World Health Organization |
| YRI | Yoruba in Ibadan, Nigeria |
|  |  |

## PART 1

## INTRODUCTION

## CHAPTER 1

An Introduction of Pharmacogenetics and the use of Massively Parallel Sequencing as a Diagnostic Tool for Personalized Medicine

Drug metabolism and response vary among individuals and the consequences of drug exposure can be helpful (i.e., the drug eliminates the physiological stimulus for which the drug was taken), harmful (i.e., the drug over- or under-corrects the physiological stimulus for which the drug was taken), or deleterious (i.e., the drug causes a series of physiological events resulting in harm or death). The realization that humans have individualized responses to exogenous compounds date back to Ancient Greece, Egypt, and Rome where black spots on fava beans were associated with death. Priests recommended that certain people abstain from ingesting products derived from the fava plant (Meletis 2011). "Favism" was later characterized as the hemolytic anemias resulting from glucose-6-phosphate dehydrogenase deficiencies common to Central Africa and southwest Asia (Luzzatto, et al. 2016). Taste blindness studies of the early 1930s were performed by Arthur L. Fox (Fox 1932 and Wooding 2006). He and his colleagues accidentally ingested phenylthiocarbamide (PTC) powder and while most of the lab reported a bitter taste in their mouths, Fox could taste nothing. He further investigated this anomaly by testing responses to PTC in a larger cohort and grouped individuals into two categories: tasters and nontasters. In the 1950s, the underlying genetic factors influencing response to normal drug dose were explored by an interdisciplinary group of scientists. Early work focused on developing accurate and precise methods for genotyping, measuring enzyme activity, drug concentrations, and metabolite concentrations, and identifying networks of drug response and metabolism proteins. In 1975, accidental ingestion of an experimental chemical once again revealed a hallmark observation. Smith and his colleagues consumed approximately 32 mg of debrisoquine, a sympathicolytic antihypertensive drug (Smith 1986). His colleagues experienced no negative response to the accident but Smith reported severe orthostatic hypotension with blood pressure dropping to
$70 / 50 \mathrm{mmHg}$. His symptoms lasted almost two days and were later attributed to genetic predisposition to poor metabolism of debrisoquine. During this time, the Smith and Eichelbaum research groups independently identified and characterized the cytochrome p450 mono-oxygenase (CYP450) enzyme polymorphisms related to drug oxidation (Fox 1932; Eichelbaum, et al. 1979; Smith 1986; Meyer 2004). This discovery was significant due to the broad spectrum of foreign and endogenous compounds that rely on oxidation via CYP450 for action and metabolism.

Present day prescription medication use has revealed similar degrees of response variation, with certain individuals demonstrating over or under "sensitivity" to different compounds. In April, 2005, thirteen days after his birth, a male child was found dead with no anatomical anomalies (Koren, et al. 2006). The cause of death (CoD) was morphine poisoning. During investigation of a possible infanticide, elevated levels of morphine were detected in his mother's breast milk. Genetic testing revealed the mother to be a rapid metabolizer of codeine which was administered to her as an analgesic for postpartum pain. It was determined that her rapid metabolizer status produced elevated levels of morphine in her blood. She then transferred morphine to her child during breastfeeding, causing opioid toxicity and accidental neonatal death. Cases such as this one that helped clarify the manner of death (MoD) demonstrate the need of molecular autopsy, i.e., genetic analyses regarding drug response, sudden cardiac arrest, etc. to help clarify instances where CoD and/or MoD are undetermined by traditional autopsy.

In 2015, an idiosyncratic response to drugs led to a lawsuit against a large pharmaceutical company (Wu, White, Oh, and Burchard 2015). After visiting a cardiologist for a heartbeat abnormality, a Hawaiian resident of Polynesian descent was diagnosed with
significant blockage of his left anterior and circumflex arteries. His cardiologist prescribed 75 mg of clopidogrel per day for the next six months. Clopidogrel is a platelet aggregation inhibitor used to treat stroke and myocardial infarction (i.e., heart attack). Thirty days after the prescription was written, the patient experienced a severe heart attack. It was later discovered that the 75 mg dose was deemed appropriate for the $\sim 95 \%$ of clinical trial participants of European ancestry but clopidogrel efficacy was never evaluated in Pacific Islander populations. This group of individuals has an exceedingly high frequency ( $80 \%$ ) of the allele conferring poor clopidogrel metabolism. Consequently, 75 mg of clopidogrel provide no significant reduction of stroke or heart attack risk in native Hawaiian individuals. This case also highlights individual variation in drug response due in part to an individual's genetics.

Pharmacogenetics, known as the elucidation of genetic factors responsible for variable drug responses, is an emerging interdisciplinary field and is the focus of this dissertation. Variation to drug therapy can have three outcomes: (1) the patient receives the desired effect; (2) the drug has no effect on the patient; or (3) the drug causes adverse reactions in the patient, e.g., death. Response to drugs and notable cases such as those mentioned above have been at the forefront of healthcare for some time and, more recently, have become a major interest of the toxicology, psychiatry, neuroscience, and forensic science communities (Bock, et al. 1994; Broly and Meyer 1993; Garrod 1996; Leppert 2011; Lam, et al. 2014; Baber, et al. 2015).

A logical target for understanding the molecular basis of drug metabolism was the CYP450 gene family, initially described by Smith and Eichelbaum (Smith 1986; Eichelbaum, et al. 1979; Meyer 2004), which encodes proteins responsible for a large portion of hepatic phase I drug metabolism (Slaughter and Edwards 1995; Ingelman-Sundberg 2003; Lewis 2004; Ingelman-Sundberg, et al. 2007). Phase I metabolism of a drug occurs in the liver and involves
at least one chemical reaction to increase the hydrophillicity of a compound, typically by the addition of a hydroxyl group or removal of a methyl group. CYP450 is a super-family of hemoproteins with a maximum light absorption at 450 nm when reduced and complexed with carbon monoxide (Ortiz de Montellano 2005). The heme complex acts as a cofactor for Phase I metabolic reactions and typically resides adjacent to the enzyme active site deep within its three-dimensional structure (Figure 1). This super-family is partially responsible for varying degrees of drug response across ethnic populations with African groups showing the most diversity and widest range of affect (Polimanti, et al. 2012). There are more than 50 unique enzymes within the CYP450 super-family (Table 1), all of which are essential for reduction of foreign and endogenous compound bioavailability. Of particular interest is CYP450 family 2 subfamily D polypeptide 6 (CYP2D6), which is responsible for approximately $30 \%$ of phase I metabolism of endogenous and foreign compounds (Ingelman-Sundberg 2005; Leppert 2011; Hicks, et al. 2013; Crews, et al. 2014). The CYP2D locus contains three homologous genes: CYP2D8 pseudogene (CYP2D8P), CYP2D7P, and CYP2D6 located in a $\sim 45 \mathrm{~kb}$ region of chromosome 22 (Figure 1; Eichelbaum, et al. 1987; Kimura, et al. 1989; Gough, et al. 1993). CYP2D6 is the only active protein produced from this locus. The enzyme accounts for a relatively small amount of hepatic CYPs but is responsible for phase I metabolism of about $25 \%$ of current market drugs, converting them from pro-drug to active metabolite (e.g., codeine to morphine), active drug to active metabolite (e.g., oxycodone to oxymorphone), or active drug to inactive metabolite (e.g., nortriptyline and amitriptyline tricyclic antidepressants to their inactive (Z)-10-hydroxylated metabolites) (Ingelman-Sundberg 2005; IngelmanSundberg, et al. 2007; Leppert 2011). Accidental overdose and idiosyncratic drug responses have been associated with variable MPs: poor (PM), intermediate (IM), extensive/normal
(EM/NM), and ultra-rapid (UM), typically described using a toxicologically determined ratio of pro-drug to active metabolite but are also predicted to some degree genetically based on CYP2D6 polymorphisms (Zhou, et al. 2008; Hiratsuka 2012; Sistonen, et al. 2012; Weber, et al. 2012).


Figure 1. Computationally predicted three dimensional structure of CYP2D6 encoded by the wild-type $*$ allele ( $* 1$, sub-image A) and a mutant, decreased function allele ( $* 10$, sub-image B). Sub-image C shows the CYP2D locus which contains the CYP2D6 gene and two pseudogenes, CYP2D7 and CYP2D8. Images modified from Black, et al. (2012) and He, et al. (2016).

Table 1. A list of 57 functional human cytochrome p450 genes; table modified from Zhou, et al. (2016).

| Gene | Alias | Names | Chromosomal Location | Substrates/Function | Amino Acids | Exons |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP1A1 | AHH; AHRR; CP11; CYP1; $\begin{gathered} P 1-450 ; P 450- \\ C ; P 450 D X \end{gathered}$ | Cytochrome P450 1A1; CYP1A1; cytochrome P450-C; cytochrome P450-P1; cytochrome P450 form 6; xenobiotic monooxygenase; aryl hydrocarbon hydroxylase; flavoprotein-linked monooxygenase; dioxin-inducible cytochrome P1-450 | 15q24.1 | Drugs, procarcinogens, steroids, and fatty acids | 512 | 7 |
| CYP1A2 | $\begin{gathered} C P 12 ; P 3-450 ; \\ P 450(P A) \end{gathered}$ | Cytochrome P450 1A2; CYP1A2; P450 form 4; cytochrome P450 4; cytochrome P450; cytochrome P450-P3; dioxin-inducible P3-450; microsomal monooxygenase; xenobiotic monooxygenase; aryl hydrocarbon hydroxylase; flavoprotein-linked monooxygenase | 15q24.1 | Drugs, fatty acids, and steroids | 516 | 7 |
| CYP1B1 | $\begin{gathered} C P 1 B ; G L C 3 A ; \\ \text { CYP1B1; } \\ \text { P4501B1 } \end{gathered}$ | Cytochrome P450 1B1; microsomal monooxygenase; xenobiotic monooxygenase; aryl hydrocarbon hydroxylase; flavoprotein-linked monooxygenase | 2p22.2 | Drugs, procarcinogens, steroids, and fatty acids | 543 | 3 |
| CYP2A6 | $\begin{gathered} \text { CPA6; CYP2A; } \\ \text { CYP2A3; } \\ \text { P450PB; } \\ \text { CYPIIA6; } \\ \text { P450C2A } \end{gathered}$ | Cytochrome P450 2A6; cytochrome P450(I); cytochrome P450 IIA3; coumarin 7-hydroxylase; xenobiotic monooxygenase; 1,4-cineole 2-exomonooxygenase; flavoproteinlinked monooxygenase | 19q13.2 | Drugs and steroids | 494 | 9 |
| CYP2A7 | $\begin{gathered} \text { CPA7; CPAD; } \\ \text { CYP2A; } \\ \text { CYP11A7; } \\ \text { P450-IIA4 } \end{gathered}$ | Cytochrome P450 2A7; cytochrome P450IIA4; cytochrome P450 IIA4 | 19q13.2 | Xenobiotics, steroids, and fatty acids | 494 | 9 |
| CYP2A13 | $\begin{gathered} \text { CPAD; } \\ \text { CYP2A; } \\ \text { CYPIIA13 } \end{gathered}$ | Cytochrome P450 2A13 | 19q13.2 | Drugs and other xenobiotics | 494 | 9 |
| CYP2B6 | $\begin{gathered} C Y P 2 B ; C Y P \\ 2 B 7 ; C Y P \\ 2 B 7 P \end{gathered}$ | Cytochrome P450 2B6; cytochrome P450 IIB; 11,4-cineole 2-exomonooxygenase | 19q13.2 | Drugs, steroids, and fatty acids | 491 | 9 |
| CYP2C8 | CYP 2C8 | Cytochrome P450 2C8; P450 form <br> 1; cytochrome P450 IIC2; <br> cytochrome P450 MP-12; <br> cytochrome P450 MP-20; <br> cytochrome P450 form 1; <br> microsomal monooxygenase; <br> xenobiotic monooxygenase; S- <br> mephenytoin 4-hydroxylase; <br> flavoprotein-linked monooxygenase | 10q23.33 | Drugs, steroids, and fatty acids | 490 | 9 |
| CYP2C9 | СРС9; СYР2С; <br> CYP2C10; <br> CYPIIC9; <br> P450IIC9 | Cytochrome P450 2C9; cytochrome P-450MP; cytochrome P450 PB-1; microsomal monooxygenase; xenobiotic monooxygenase; flavoprotein-linked monooxygenase | 10 q 24 | Drugs, steroids, and fatty acids | 490 | 9 |
| CYP2C18 | $\begin{aligned} & \text { CYP 2C; CYP } \\ & \text { 2C17; CYPI; } \\ & \text { P45011C17; } \\ & \text { P450-6B/29C } \end{aligned}$ | Cytochrome P450 2C18; microsomal monooxygenase; unspecific monooxygenase; flavoprotein-linked monooxygenase; S-mephenytoin hydroxylase associated cytochrome P450 | 10q24 | Drugs, steroids, and fatty acids | 490 | 9 |

Table 1 (continued). A list of 57 functional human cytochrome p450 genes; table modified from Zhou, et al. (2016).

| Gene | Alias | Names | Chromosomal Location | Substrates/Function | Amino Acids | Exons |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP2C19 | CYP2C; CYPJ; P450C2C; CYPIIC17; CYPIIC19; P450IIC19 | Cytochrome P450 2C19; cytochrome p450-11A; cytochrome P450-254C; cytochrome P450 II C; microsomal monooxygenase; xenobiotic monooxygenase; mephenytoin 4'-hydroxylase; Smephenytoin 4-hydroxylase | 10q24.1-q24.3 | Drugs | 490 | 9 |
| CYP2D6 | CYD6; CYP2D; CYP2D7AP; CYP2D7BP; CYP2D7P2; CYP2DL1; CYPIID6; P450C2D; P450DB1; CYP2D8P2; P450-DB1 | Cytochrome P450 2D6; cytochrome P45-DB1; microsomal monooxygenase; xenobiotic monooxygenase; debrisoquine 4hydroxylase | 22q13.1 | Drugs | 497 | 10 |
| CYP2E1 | $\begin{gathered} \text { CYP2E; CYE1; } \\ \text { P450-J; } \\ P 4502 C 2 E \end{gathered}$ | Cytochrome P450 2E1; cytochrome P450-J; microsomal monooxygenase; xenobiotic monooxygenase; 4-nitropheno 2hydroxylase; flavoprotein-linked monooxygenase | 10q26.3 | Drugs, ethanol, and procarcinogens | 493 | 9 |
| CYP2F1 | CYP2F; C2F1 | Cytochrome P450 2F1; CYPIIF1; <br> microsomal monooxygenase; xenobiotic monooxygenase; flavoprotein-linked monooxygenase | 19q13.2 | Drugs and coumarins | 491 | 11 |
| CYP2J2 | CP J2 | Cytochrome P450 2J2; CYPIIJ2; <br> microsomal monooxygenase; arachidonic acid epoxygenase; flavoprotein-linked monooxygenase | 1p31.3-p31.2 | Fatty acids | 502 | 9 |
| CYP2R1 | CYP 2R1 | Vitamin D 25-hydroxylase; cytochrome P450 2R1 | 11p15.2 | Vitamin D | 501 | 8 |
| CYP2S1 | CYP 2S1 | Cytochrome P450 2S1; CYPIIS1 | 19q13.1 | Xenobiotics | 504 | 9 |
| CYP2U1 | $\begin{gathered} \text { SPG49; } \\ \text { SPF56; } \\ \text { P450TEC } \end{gathered}$ | Cytochrome P450 2U1; spastic paraplegia 49 | 4 q 25 | Amino acids, dehydroepiandrosterone, and long-chain fatty acids | 544 | 5 |
| CYP2W1 | CYP 2W1 | Cytochrome P450 2W1; CYPIIW1 | 7p22.3 | Unknown | 490 | 10 |
| CYP3A4 | HLP; CP33; CP34; СYP3A; NF-25; CYP3A3; P340C3; CYPIIIA3; CYPIIIA4; P450PCN1 | Cytochrome P450 3A4; 1,8-cineole 2-exo-monooxygenase; steroidinducible P450-III; albendazole monooxygenase; albendazole sulfoxidase; cytochrome P450 3A3; cytochrome P450 HLp; cytochrome P450 NF-25; cytochrome P450 subfamily IIIA (nifedipine oxidase) polypeptide 3; cytochrome P450 subfamily IIIA (nifedipine oxidase) polypeptide 4; cytochrome P450PCN1; glucocorticoid-inducible P450; nifedipine oxidase; quinine 3-monooxygenase; taurochenodeoxycholate 6- $\alpha-$ hydroxylase | 7q21.1 | Drugs, steroids, and fatty acids | 503 | 14 |

Table 1 (continued). A list of 57 functional human cytochrome p450 genes; table modified from Zhou, et al. (2016).

| Gene | Alias | Names | Chromosomal <br> Location | Substrates/Function | Amino <br> Acids |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Exons |  |  |  |  |

Table 1 (continued). A list of 57 functional human cytochrome p450 genes; table modified from Zhou, et al. (2016).

| Gene | Alias | Names | Chromosomal Location | Substrates/Function | Amino Acids | Exons |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP5A1 | TXBAS1; TS; TXS; CYP5; TXAS; THAS; GHOSAL; BDPLT14 | Thromoxane A-synthase; TXA synthase; cytochrome P450 5A1 | 7q34-q35 | Thromboxane synthesis | 534 | 18 |
| CYP7A1 | $\begin{gathered} \text { CP7A; CYP7; } \\ \text { CYPVII } \end{gathered}$ | Cholesterol 7 $\alpha$-monooxygenase; cytochrome P450 7A1; cholesterol $7 \alpha$-hydroxylase | 8q11-q12 | Conversion of cholesterol to bile acids | 504 | 6 |
| CYP7B1 | $\begin{gathered} C P 7 B ; C B A S 3 ; \\ S P G 5 A \end{gathered}$ | 25-Hydroxycholesterol 7 $\alpha$ hydroxylase; cytochrome P450 7B1; oxysterol 7 $\alpha$-hydroxylase | 8 q 21.3 | Conversion of cholesterol to bile acids | 506 | 6 |
| CYP8A1 | CYP 8; PGIS; PTGI; PTGIS | Prostacyclin synthase; prostaglandin I2 synthase | 20q13.13 | Isomerization of PGH2 to prostacyclin | 500 | 10 |
| CYP8B1 | CYP 12; $C P 8 B$ | $7 \alpha$-Hydroxycholes-4-en-3-one $12 \alpha$ hydroxylase; CYPVIIIB1; cytochrome P450 8B1; sterol $12 \alpha$-hydroxylase | $3 \mathrm{p} 22-\mathrm{p} 21.3$ | Steroids | 501 | 1 |
| CYP11A1 | CYP 11A; <br> CYPXIA1; <br> P450SCC | Mitochondrial cholesterol sidechain cleavage enzyme; steroid 20-22-lyase; cytochrome P450 11A1 | $15 \mathrm{q} 23-\mathrm{q} 24$ | Side-chain cleavage of cholesterol pregnenolone | 521 | 12 |
| CYP11B1 | $\begin{gathered} \text { CYP 11B; FHI; } \\ \text { CPN1; } \\ \text { P450SCC } \end{gathered}$ | Mitochondrial cytochrome P450 11B1; CYPXIB1; cytochrome P450C11; steroid $11 \beta$ hydroxylase | 8q21.3 | Steroids | 503 | 11 |
| CYP11B2 | $\begin{gathered} \text { CYP 11BL; } \\ \text { CYP 11B; } \\ \text { CPN2; } \\ \text { ALDOS; } \\ \text { CYPXIB2; } \\ \text { P450C18; } \\ \text { P450aldo } \end{gathered}$ | Mitochondrial cytochrome P450 11B2; cytochrome P450C18; aldosterone synthase; steroid $11 \beta$-monooxygenase; steroid 11 $\beta / 18$-hydroxylase; aldosterone-synthesizing enzyme | 8q21-q22 | Steroids, especially productions of aldosterone | 503 | 9 |
| CYP17A1 | $\begin{aligned} & \text { CYP 17; } \\ & \text { CPT17; } \\ & \text { S17AH; } \\ & \text { P450C17 } \end{aligned}$ | Steroid $17 \alpha$-hydroxylase $/ 12,20$ lyase; cytochrome P450C17; steroid $17 \alpha$-monooxygenase; $17 \alpha$-hydroprogesterone aldolase | 10q24.3 | Steroids, especially conversion of pregnenolone and progesterone | 508 | 8 |
| CYP19A1 | CYP 19; ARO; <br> ARO1; CPV1; <br> CYAR; <br> CYPXIX; P- <br> 450AROM | Aromatase; estrogen synthase; cytochrome P-450AROM; cytochrome P450 19A1; microsomal monooxygenase; flavoprotein-linked monooxygenase | 15q21.1 | Steroids, especially formation of aromatic C18 estrogens and C19 androgens | 503 | 14 |
| CYP20A1 | CYP-M | Cytochrome P45020A1; <br> cytochrome P450 monooxygenase | 2q33.2 | Unknown | 462 | 14 |
| CYP21A2 | $\begin{gathered} \text { CYP21; } \\ \text { CYP21B; } \\ \text { CAH1; CPS1; } \\ \text { CA21H; } \\ \text { P450c21B } \end{gathered}$ | Steroid 21-hydroxylase; 21Ohase; cytochrome P450XXI; cytochrome P450-C21B | 6p21.3 | 21-Hydroxylation of steroids; required for adrenal synthesis of mineralocorticoids and glucocorticoids | 495 | 11 |

Table 1 (continued). A list of 57 functional human cytochrome p450 genes; table modified from Zhou, et al. (2016).

| Gene | Alias | Names | Chromosomal Location | Substrates/Function | Amino Acids | Exons |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP24A1 | CP24; CYP24; HCAI; P450- <br> CC24; cytochrome P450 family 24 subfamily A member 1; HCINF1 | Mitochondrial 25hydroxyvitamin D3-24-hydroxylase | 20q13.2 | Vitamin D degradation | 514 | 12 |
| CYP26A1 | CP26; CYP26; P450RAI; <br> P450RAII; cytochrome P450 family 26 subfamily A member 1 | 4-Hydroxylate; 18hydroxylase | 10q23.33 | Retinoic acid hydroxylase | 497 | 8 |
| CYP26B1 | CYP26A2; P450RAI-2; P450RAI2; RHFCA; <br> cytochrome P450 family 26 subfamily B member 1 | Broad acting hydroxylase; retinoic acid monooxygenase | 2p13.2 | Retinoic acid hydroxylase | 512 | 8 |
| CYP26C1 | FFDD4; cytochrome P450 family 26 subfamily C member 1 | Broad acting hydroxylase; retinoic acid monooxygenase | 10 q 23.33 | Retinoic acid hydroxylase | 522 | 7 |
| CYP27A1 | CP27; CTX; CYP27; <br> cytochrome P450 family 27 <br> subfamily A member 1 | Sterol 27hydroxylase | $2 q 35$ | Bile acid biosynthesis | 531 | 11 |


| CP2B; CYP1; CYP1alpha; |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | CYP27B; P450c1; PDDR; | 25-Hydroxyvitamin |  | Vitamin D3 1 $\alpha$ |  |
| CYP27B1 | VDD1;VDDR; VDDRI; VDR; | D3 $1 \alpha$-hydroxylase; | 12q14.1 | hydroxylase; activates | 508 |
|  | cytochrome P450 family 27 | $1 \alpha$-hydroxylase |  | vitamin D3 |  |
|  | subfamily B member 1 |  |  |  |  |


| CYP27C1 | cytochrome P450 family 27 <br> subfamily C member 1 | Sterol <br> monooxygenase | $2 q 14.3$ | Unknown | 372 | 9 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP39A1 | cytochrome P450 family 39 <br> subfamily A member 1 | Oxysterol 7- $\alpha-$ <br> hydroxylase 2 | 6 p 12.3 | $7 \alpha$-hydroxylation of 24- <br> hydroxycholesterol | 469 |  |

These MPs have been used as an adjunct to guide prescription medication practices and have provided critical information in legal cases to describe CoD and/or MoD. Genetic predictions of MP are based on the presence of one or more causal CYP2D6 polymorphisms (Gaedigk, et al 2008 and 2016). Reference to the haplotype of polymorphisms within CYP2D6 is known as a star $\left(^{*}\right)$ allele (Figure 2). As of 2015, over 100 different * alleles and 18 full gene duplications have been characterized that impart metabolic phenotype differences (Marez, et al. 1997; Gaedigk, et al. 2008; Crews, et al. 2014; Gaedigk, et al. 2016). A number of * alleles have been characterized based on the presence of single SNPs or INDELs while others contain variation along the length of the gene. For example, CYP2D6*7 contains 2935A>C (rs5030867; Figure 1) only while CYP2D6*28 contains 19G>A (rs72549358), 1661G>C (rs1058164), 1704C>G (rs78482768), 2850C>T (rs16947), and 4180G>C (rs1135840). The causal aspect of carrying one or more SNPs or INDELs relative to the reference genomes is risk of altering the amino acid sequence (i.e., a non-synonymous mutation) or introducing a premature stop codon (i.e., a missense mutation) and thereby changing the protein and/or active site structure. CYP2D6 * alleles have been used to characterize MP distribution in human populations using the activity score (AS) approach. AS is a qualitative measure of MP by which individual alleles of the CYP2D6 genotype (or individual haplotypes of the CYP2D6 * allele diplotype) are assigned a value from 0-1, based on experimentally observed enzyme activity, and summed (Table 2) (Gaedigk, et al. 2016). For example, a NM/EM individual carries the CYP2D6 diplotype $* 1 / * 4 ; * 1$ is the fully functional wild-type allele and is assigned an AS of 1 while $* 4$ is non-functional and is assigned an AS of 0 . The sum of the AS for each * allele is the AS for this individual. Note that this example individual carries an allele conferring a fully
functional enzyme so he/she is considered an NM/EM even though *4 abolishes enzyme activity (Table 2).


Figure 2. Example CYP2D6 star (*) alleles. Blue rectangles and horizontal lines represent CYP2D6 exons and introns, respectively; single nucleotide polymorphism (SNP) rs numbers are provided for select * allele defining loci; designated SNP alleles are in relative to the hg19 reference genome. CYP2D6*1A is the wild type * allele; CYP2D6*7 and CYP2D6*10A demonstrate how individual SNPs, or a collection of SNPs along the length of the gene, confer different * alleles.

Table 2. Metabolizer phenotype (MP) defined by CYP2D6 activity score. Table modified from data presented by Crews, et al. 2014. Asterisks indicate CYP2D6 star $\left(^{*}\right.$ ) alleles; up arrows ( $\uparrow$ ) indicate increased function alleles, down arrows ( $\downarrow$ ) indicate decreased function alleles, horizontal double sided arrows $(\leftrightarrow)$ indicate normal function alleles, and horizontal bars ( - ) indicate null/no function alleles. Placement of gene duplications into a metabolizer phenotype category is based on the assumption of duplication producing one additional * allele (three total $*$ alleles). This categorization may change if the duplication event results in more than three alleles for an individual.

| MP | $\begin{array}{c}\text { Percent of } \\ \text { Patients }\end{array}$ | $\begin{array}{c}\text { Activity } \\ \text { Score }\end{array}$ | Definition |
| :---: | :---: | :---: | :--- | \(\left.\begin{array}{c}Example <br>

Genotype\end{array}\right]\)

CYP2D6 * alleles encoding normally active protein confer the EM phenotype when present in homozygous normal/normal, heterozygous normal/decreased function, or heterozygous normal/null genotypes. CYP2D6*1 and its derivatives $(* 1 \mathrm{~A}, * 1 \mathrm{~B}, * 1 \mathrm{C}, * 1 \mathrm{D}$, and
*1E) encode normal fully functional enzymes (Kimura, et al. 1989; Marez, et al. 1997; Sachse, et al. 1997). The $C Y P 2 D 6^{*} 1$ has allele frequencies of $0.32,0.50,0.35,0.49,0.38$, in the African, Admixed American, East Asian, South Asian, and European global populations, respectively. Also encoding a fully functional enzyme is CYP2D6*2 which has at least twelve sub-types $(* 2 \mathrm{~A}$ through $* 2 \mathrm{H}$ and $* 2 \mathrm{~J}$ through $* 2 \mathrm{M})$ all characterized by the presence of the $2850 \mathrm{C}>\mathrm{T}(\mathrm{rs} 16947)$ and $4180 \mathrm{G}>\mathrm{C}(\mathrm{rs} 1135840)$ SNPs which do not alter protein function relative to CYP2D6*1. This allele is quite frequent in global populations and may be more common than the reference allele in some populations (Marez, et al. 1997; Gaedigk, et al. 2016). Other alleles resulting in normal enzyme function include CYP2D6*27, *33, *35, *39, *45 (debated), and *48.

Null * alleles do not encode an active form of CYP2D6 and, when found as homozygous null/null or heterozygous null/decreased function genotypes, confer the PM phenotype in various ways. The mechanisms are: (1) Disruption of reading frame caused by INDELs and SNPs which generate premature stop codons or altered protein folding, such as 2549delA (rs35742686), which produces CYP2D6*3 (Kagimoto, et al. 1990). CYP2D6*3 encodes a truncated protein product and was first detected in Caucasian (frequency of 0.013) PMs but also has been observed in African Americans with an allele frequency of 0.0031 (Crews, et al. 2014); (2) Full-length non-functional * alleles due to SNPs and/or INDELs that are tolerated during splicing and protein folding. CYP2D6*12, *14, and *18, for example, contain $124 \mathrm{G}>\mathrm{A}$ (no rs number), 1758G>A (rs5030865), and 4125-4133dupGTGCCCACT (rs765776661), respectively, which do not disrupt formation of CYP2D6 but alter amino acid composition in such a way that renders the protein completely inactive (Marez, et al. 1996; Yokoi, et al. 1006; Wang, et al. 1999); (3) Deletion of CYP2D6 as seen in *5 which has a 5-
$7 \%$ allele frequency across most ethnic groups (Gaedigk, et al. 1991; Steen, et al. 1995); and (4) Formation of a hybrid gene with the highly homologous CYP2D7P as seen in *11 (Marez, et al. 1995; Skierka, et al. 2012).

A number of CYP2D6 * alleles give rise to significantly decreased enzyme activity including, but not limited to, $C Y P 2 D 6 * 10, * 14, * 17, * 41$, and $* 51$. The consequence of harboring these variant * alleles is typically enzyme instability, poor substrate recognition by the enzyme active site, and reduced affinity of the enzyme for a given substrate (Zhou 2009). The IM phenotype occurs when these alleles are found in heterozygous null/decreased function genotypes. Decreased function alleles are probably the most diverse in terms of population association. For example, CYP2D6*10 (Figure 1) has a frequency near 0.43 in East Asian (Japanese and Korean) populations but only 0.050 in Caucasian and African American populations (Leathart, et al. 1998; Bradford 2002). Conversely, *17 is observed at frequencies of 0.090 (Ethiopian) and 0.34 (Zimbabwean) in African populations but is low or nearly absent in the American, East Asian, and European populations (average frequencies of 0.026, $0.00010,0.0036$, respectively [Bradford 2002]).

There are two forms of increased function CYP2D6 * alleles come in two forms: (1) alleles which confer increased affinity of the enzyme for the substrate and (2) duplicated functional alleles. To date, $C Y P 2 D 6 * 53$ is the only * allele encoding an enzyme that decreases required drug concentration for half-maximal enzyme saturation $\left(\mathrm{K}_{\mathrm{m}}\right)$ by any notable quantity (73\% decrease with bufuralol-10-hydroxylation) (Ebisawa, et al. 2005; Sakuyama, et al. 2005). This allele is rare with frequencies of 0.0050 in a Mexican population sampled by Contreras, et al. 2011 and 0.0017 in a Japanese population sampled by Ebisawa, et al. 2005. Gene duplications have been reported for $C Y P 2 D 6^{*} 1, * 2, * 4, * 9, * 10, * 17$, and $* 35$, each of which
(except *9 and *17) have multiple subtypes. Approximately $5.21 \%$ of the total United States population exhibits duplications with three or more copies of CYP2D6, though the exact number and frequency of each is typically not reported. The UM phenotype may arise if the duplicated allele is fully functional and paired with a decreased (*10/*1x2; AS $=2.5$ ), normally $(* 2 / * 1 \times 2 ; \mathrm{AS}=3)$, or increased $(* 53 / * 1 \times 2 ; \mathrm{AS}=3.5)$ function allele. Alternatively, a gene duplication may not confer the UM phenotype if the duplicated allele is functionally deficient and paired with a normally active $(* 1 / * 10 \times 2 ; \mathrm{AS}=2)$ or another functionally deficient $(* 9 / * 10 \times 2 ; \mathrm{AS}=1.5)$ allele. Gene duplications and the resulting MP are listed in Table 2 (Zhou 2009; Beoris, et al. 2016).

Recently Gaedigk, et al. (2016) used AS to characterize intra-MP variability in world populations in the absence of toxicological and/or pharmacological data (Figure 3). While previously described in select studies (Sistonen, et al. 2007; Gaedigk, et al. 2008; Chen, et al. 2015) as an additional observation, this study was the first to highlight variation within the four major MPs. Figure 3a divides the EM (or NM) population into five distinct sub-categories based on AS from 1 to 2 and the genotype responsible for conferring that AS.


Figure 3. CYP2D6 phenotype prediction from genotype data (image borrowed from Gaedigk, et al. 2016. An activity score (AS) was assigned to each genotype (no, $\downarrow$, $\leftrightarrow$, and $\uparrow$ indicate genotypes with no-, decreased-, normal-, and/or increased-function allele combinations, respectively). Panel A shows average frequencies for the different allele combinations and their respective phenotype classifications into poor (gPM), intermediate (gIM), normal-slow (gNMS), normal-fast (gNM-F), and ultrarapid (gUM) metabolizer groups. The prefix " g " indicates that the phenotype is predicted from genotype. For panel B, genotypes giving rise to $\mathrm{AS}=1$ or $\mathrm{AS}=2$ were grouped as indicated. Panel C depicts the translation of genotype or AS into phenotype according to the classification used in Clinical Pharmacogenetics Implementation Consortium guidelines. Note that genotypes falling into the AS = 1 group are inconsistently classified as gIM or gNM throughout the literature.

While CYP2D6 plays a substantial role in opiate metabolism, SNPs in other genes can further define metabolizer status (Figure 4; Diatchenko, et al. 2005; Lam, et al. 2014; Bastami, et al. 2014; Baber, et al. 2015). The personalized medicine community has more recently been investigating genetic variability of trans-acting metabolic proteins, in particular those implicated in analgesic response, opiate metabolism, and addiction (Rakvåg, et al. 2005; Fujita, et al. 2010;Yuferov, et al. 2010; Crist and Berrettini 2013;Lam, et al. 2014; Baber, et al. 2015; Bastami, et al. 2014; Altar, et al. 2015). These additional genes of interest encode opioid receptor mu 1 (OPRM1; mu opioid receptor 1), uridine diphosphate glucuronosyltransferase family 1 polypeptide B7 (UGT2B7), adenosine triphosphate (ATP) binding cassette subfamily B number 1 (ABCB1; p-glycoprotein; multidrug resistance protein 1), and catechol-Omethyltransferase (COMT). OPRM1 serves as the primary action site for commonly used opioids and morphine, a common primary metabolite. UGT2B7 converts morphine to morphine-6-glucuronide (M6G); these two compounds are the primary cause of the analgesic effect of opiates. ABCB1 encodes p-glycoprotein, a membrane-associated transporter responsible for the efflux of morphine from the brain, gastrointestinal tract, kidneys, and liver. Finally, COMT interacts with the opioid receptor mechanism and modulates pain response through catecholamine breakdown. Polymorphisms within these genes have been demonstrated to impact opiate metabolism by altering the performance of their protein products (Table 3) (Lam, et al. 2014; Baber, et al. 2015). Although considerably less variable than CYP2D6 based on currently employed methodologies, SNPs within UGT2B7, ABCB1, OPRM1, and COMT provide additional genetic information on how various aspects of opiate metabolism occur within the body and the phenotypic variability in those processes.


Figure 4. Participation of the selected proteins in analgesia production following opiate administration. Codeine is used as an example opiate; proteins of interest are in red text.

Table 3. Commonly typed causal single nucleotide polymorphisms (SNPs) in CYP2D6, OPRM1, UGT2B7, ABCB1, and COMT (Diatchenko, et al. 2005; Lam, et al. 2014). Many COMT SNPs are not independently associated with variable enzyme activity, but haplotypes of multiple SNPs in this gene have shown positive linear correlations with enzyme activity. The CYP2D6 SNPs are a representative sampling of those responsible for conferring the four major metabolizer phenotypes; asterisks indicate CYP2D6 star $\left(^{*}\right)$ alleles.

| Gene | SNP rs Number | Enzyme Activity |
| :---: | :---: | :---: |
| CYP2D6 | - | *1A, Wild type, considered fully functional |
|  | rs16947, rs1135840 | *2D, Normal function except when duplicated |
|  | rs35742686, rs1135824 | *3A, Nonfunctional, frameshift mutation |
|  | rs3892097, rs28371733 | *4, Nonfunctional, splicing defect |
|  | - | *5, Nonfunctional, complete gene deletion |
|  | rs5030655 | *6, Nonfunctional, frameshift mutation |
|  | rs5030656 | *9, Partially functional |
|  | rs1065852 | *10, Partially functional |
|  | rs28371706, rs16947 | *17, Partially functional |
| OPRM1 | rs1799971 | Decreased |
| UGT2B7 | rs7439366 | Increased |
|  | rs62298861 | Increased |
| ABCB1 | rs2229109 | Unsure |
|  | rs1128503 | Decreased |
|  | rs2032582 | Decreased |
|  | rs1045642 | Decreased |
| COMT | rs4633 | Not independently associated with activity |
|  | rs4818 | Not independently associated with activity |
|  | rs4680 | Decreased |
|  | rs2239393 | Not independently associated with activity |
|  | rs165728 | Not independently associated with activity |
|  | rs165599 | Not independently associated with activity |

Phase II metabolism also occurs in the liver and is characterized by additional chemical reactions, such as glucuronidation, acetylation, and sulfation, that further increase the hydrophillicity of toxins and facilitate their distribution and/or excretion from the body in the urine or feces (e.g., hormones are readily glucuronidated to minimize the energy required to distribute them throughout the body). The UGT super-family is involved in phase II drug metabolizing glucuronidation reactions which increase the polarity of xenobiotics and
endogenous toxins by conjugating to them the glucuronic acid moiety of uridine diphosphate glucuronic acids. The resulting glucuronic acids are more easily excreted from the body due to increased solubility (Guillemette 2003). Studies of the UGT super-family reveal its involvement in approximately $35 \%$ of all drugs which undergo phase II metabolism (Evans and Relling 1999). UGT2B7 is found on chromosome four, contains six exons, encodes one specific UGT enzyme found mostly in the brain, pancreas, lungs, gastro-intestinal tract, mammary glands, and liver, and is often recognized for its broad substrate specificity. The polymorphic nature of this enzyme was described initially by Ritter, et al. (1990), who performed the original protein purification and amino acid sequence prediction. Saeki, et al. (2004) identified twenty-one polymorphisms within the gene region of Japanese individuals, relative to the reported sequence by Ritter, et al. (1990), which led to characterization of four distinct $U G T 2 B 7$ * alleles (*1 through *4) and a number of distinct subtypes (*1a-*1k, *2a$2 \mathrm{~g}, * 3$, and $* 4$ ). Functional characterization of $*$ alleles has shown that genotypes containing *2 produce glucuronic acid metabolites at higher concentrations than the *1 wild type, though most studies show that concentrations remain within safe therapeutic windows for a number of drugs (Saeki, et al. 2004; Chung, et al. 2008; Du, et al. 2016; Vandenbossche, et al. 2014). Conversely, Sawyer, et al. (2003) showed that *1/*2 heterozygotes displayed the highest glucuronidation activity in terms of morphine metabolism. UGT2B7*3 and *4 are characterized by the A71S and D398N amino acid changes, respectively, and show reduced glucuronidation activity (Wang, et al. 2011; Yuan, et al. 2015).

ABCB1 encodes p-glycoprotein (also called multidrug resistant protein 1, MDR1), a transporter containing two homologous halves, each with six transmembrane domains (Figure 5) (Hodges, et al. 2011). The protein is an ATP-dependent translocator capable of performing
excretory and protective roles within the body by controlling drug efflux from certain tissues (e.g., limits access to the brain via the blood-brain barrier). $A B C B 1$ is found on chromosome seven and contains 29 exons, two of which are untranslated (Bodor, et al. 2005). Three important inter-ethnically variable polymorphisms have been identified within the gene, $1236 \mathrm{~T}>\mathrm{C}(\mathrm{rs} 1128503), 2677 \mathrm{~T}>\mathrm{G} / \mathrm{A}(\mathrm{rs} 2032582)$, and $3435 \mathrm{~T}>\mathrm{C}(\mathrm{rs} 1045642)$, but the literature remains inconclusive regarding phenotypic impact of one allele over another (Mathijssen, et al. 2003; Schwab, et al. 2003; Wang, et al. 2005; Leschziner, et al. 2007; Zhang, et al. 2008; Schaich, et al. 2009). Initially studied independently, these three SNPs exhibit high linkage disequilibrium (LD) and are inherited as a haplotype, frequently found in the CGC or TTT form in most populations (Hodges, et al. 2011). The four $A B C B 1 *$ alleles are defined relative to the CGC haplotype (*1); however, their use in the literature is inconsistent. For example, Kim, et al. (2001) define $A B C B 1 * 2$ as the TTT form while Kroetz, et al. (2003) defines the same * allele as the CGT form. Pharmacogenomics. Knowledge. Implementation. (PharmGKB) defines them as $A B C B 1 * 1$-CGC, *2-CGT, and *13-TTT (PharmGKB). Barratt, et al. (2012) demonstrated that individuals harboring the TTT haplotype required only $62 \%$ of the methadone required by individuals with other haplotypes.


Figure 5. Two-dimensional structure of P-glycoprotein (P-gp) and corresponding representative SNP locations within the $A B C B 1$ exonic region of the American population. This figure illustrates the approximate locations of amino acid changes along the P-gp protein resulting from non-synonymous polymorphisms. A red " X " marks the approximate location of each polymorphism identified by Kimchi-Sarfaty, et al. (2007); black dots represent the approximate locations of common amino acid changes previously reported in P-gp; exons 128 are labeled by color and nucleotide length. Image borrowed from Kimchi-Sarfaty, et al. (2007).

Opioid receptors (OPRs) are part of the G-protein coupled receptor super-family which activate downstream signaling pathways through interaction with heterotrimeric G-proteins (Waldhoer, et al. 2004). OPRM1 consists of seven transmembrane domains (Figure 6), three intra- and extra-cellular domains, and an extracellular N -terminus encoded by a gene containing 15 total exons (Waldoeher, et al. 2004). Despite the total number of exons, each transcript from OPRM1 contains only four exons. The receptor is responsible for binding natural or synthetic opioid agonists and propagating analgesia. OPRM1 spans approximately

200kb of chromosome 6, which is highly homologous with other OPRs (Diatchenko, et al. 2011). $O P R M 1$ is quite polymorphic but is not defined using the * allele designation as is used for CYP2D6, UGT2B7, and ABCB1. Approximately 3,324 polymorphisms have been identified along the $O P R M 1$ gene region, most of which have frequencies below $1 \%$. The most common SNP is A118G (rs1799971) which causes an aspartate to asparagine amino acid change at position 40 of the extracellular receptor region, resulting in poor receptor glycosylation and decreased opioid potency (Campa, et al. 2008; Ting and Schug 2016). This variant is found most frequently in Asian populations (nearly 0.50 ) and is substantially less common in Caucasians (frequency ranging from 0.08-0.17) (Janicki 2013). Studies of the phenotypic impact of low frequency polymorphisms (less than 0.05 ) are limited.


Figure 6. Naturally occurring, non-synonymous OPRM1 variants reported, and their position on the $\mu$-opioid receptor protein. Residues where an amino acid exchange occurs are indicated in red. Image borrowed from Knapman and Connor (2014).

The COMT locus resides on chromosome 22 and contains eight exons which encode the COMT enzyme responsible for metabolizing and inactivating catecholamines such as dopamine, noradrenaline, and adrenaline and regulating their propagation through synapses of the brain (Janicki 2013). Due to its responsibility of moderating analgesia and feel-good sensations, this enzyme has been a primary target for investigating underlying genetic factors associated with pain management and psychiatry (Diatchenko, et al. 2005; Webster 2008; Schacht 2016). COMT is polymorphic, but like OPRM1, is not defined using the * allele designation even though the benefits of a more standardized allele nomenclature have been suggested and demonstrated in other pharmacogenes (Diatchenko; et al. 2005; Handoko, et al. 2005). The most widely studied polymorphism in the gene region is G472A (rs4680 or rs165688) which causes the non-synonymous valine to methionine amino acid substitution at position 158 and a 3- to 4-fold decrease in COMT activity (Zubieta, et al. 2003; Ross, et al. 2008). Homozygous AA individuals have been shown to have higher ratings of pain than individuals with the AG or GG genotypes (Lotta, et al. 1995; Zubieta, et al. 2003; Rakvåg, et al. 2005; Webster 2008). Exploration of non-exonic regions of the gene also has shown positive linear correlation with certain diseases (e.g., schizophrenia); however, the collective group of SNPs has not been associated with brain expression levels in a reproducible manner (Bray, et al. 2003; Chen, et al. 2004; Christoffersen, et al. 2016).

The polymorphic natures of CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT are relatively well understood on the individual-gene level in various population groups (Cusato, et al. 2016; Gaedigk, et al. 2016; Sridharan, et al. 2016; Sutiman, et al. 2016; and Zahari, et al. 2016). However, the combined and pairwise predictive power within their gene regions has scarcely been described in healthy or affected populations. In a group of psychiatric patients,

Altar, et al. (2015) demonstrated that a combinatorial pharmacogenetics approach using allelic variations from four genes can guide antidepressant selection and predict antidepressant efficacy better than each individual gene alone. Therefore, it is reasonable to explore the relationship between other genes and develop combinatorial pharmacogenetic predictive models for drug efficacy and patient response. Bastami, et al. (2014), Lam, et al. (2014), and Baber, et al. (2015) studied CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT in various combinations in relation to codeine-based treatment and reported certain causal SNPs and their allele frequencies. While informative, these studies are based on cohorts selected for the presence of specific characteristics (e.g., abdominal hysterectomy (Bastami, et al. 2014), drug related deaths with codeine as a contributing factor (Lam, et al. 2014), and women who delivered a child via cesarean-section (Baber, et al. 2015)) with no mention of populationaffinity information as a contributing factor to variable metabolic activity resulting from allele frequency differences between/among populations. As a result, false positive associations between genotype and resulting phenotype may arise. These studies provided summary statistics for select polymorphisms in each gene but lacked the association between/among genes required for a multigenic approach to personalized medicine. Ideally, study subjects would belong to a defined population and be positively selected for the desired phenotype. Due to the presence of relatively recent founder effects and resulting minimal degree of population substructure, populations such as Finns and Ashkenazi Jews may be enriched for rare mutations relative to the overall European population (Peltonen, et al. 1999; Kere 2001; Palo, et al. 2009; Lim, et al. 2014).

CYP2D6 is highly polymorphic and there is significant variation in allele frequencies within and among populations. While exhibiting less overall variation than CYP2D6, the

UGT2B7, ABCB1, OPRM1, and COMT pharmacogenes also are phenotypically relevant. Genetic variation at these loci may affect protein activity and/or structure but the extent of this variation cannot be captured fully by existing structured SNP panels. Genome-wide association studies (GWAS) and SNP arrays rely on targeted identification or typing of known causal SNPs that have been shown to affect metabolic activity or those that are candidate enzymealtering sites. These assays lack the ability to comprehensively identify SNPs, and especially previously undescribed SNPs, within a gene (Koch 2004). Extensive variation combined with targeted approaches, that may not detect full variation, leads to less effective genotyping in the event that an individual(s) contains an allele characterized by absence of the gene (CYP2D6*5) or a rare variant not previously reported. Additionally, GWAS and SNP arrays are limited by the potential need to resequence targets to confirm allele calls (Koch 2004). Massively parallel sequencing (MPS) offers a considerable advantage over the GWAS and SNP array approaches due to a lower biased and robust generation of large amounts of sequence data, with reliable read depth (i.e., the number of times a single region of DNA is sequenced) using minimal input amounts of DNA. GWAS using SNP array data suffer from genotype ascertainment bias due to the methods of SNP inclusion during assay development (Lachance and Tishkoff 2013). These loci tend to be selected from existing DNA sequence data and may represent loci with relatively high global minor allele frequencies (e.g., 0.01) to ensure representation of a majority of global genetic variation. However, by targeting only loci with high global frequency, the assay lacks the ability to directly genotype loci that may be enriched for in the rare ancestral or diseased population in question. Use of MPS in pharmacogenetic studies enables relatively reduced genotype ascertainment bias and analysis of many targeted genomic regions (fullgene, distant regulatory elements, multiple genes, etc.) simultaneously (Xin and Wang, 2003;

Saeki, et al. 2004; Wang, et al. 2014; Ge, et al. 2016; Modaresi-Nejad, et al. 2015; Wang, et al. 2015).

There are many MPS technologies and chemistries commercially available (Figure 7) but two of the most commonly employed MPS instruments rely on sequencing-by-synthesis of clonally amplified DNA using two distinct chemistries: reversible terminators and semiconductor pH detection (Lysholm, et al. 2011). The massively parallel nature of MPS is achieved by clonal amplification of relatively small target DNA fragments on either a flow cell or bead within a micelle. The target DNA hybridizes to an oligo-covered surface and serves as a template for thousands of PCRs. This process results in a "lawn" of small clusters (MiSeq chemistry) or micro-beads coated in identical/clonal DNA clusters. Sequencing with the Illumina MiSeq Desktop Sequencer utilizes fluorescently-labeled reversible terminator deoxynucleotide triphosphates (dNTPs) (Goodwin, et al. 2016); this chemistry is employed for data generation in this dissertation. The reversible terminator ensures that only one dNTP is added to the growing chain during every flow of pooled dNTPs across the flow cell. After fluorescent signal detection via charge-coupled device (CCD) cameras, the terminator is removed and the next flow is performed, adding one additional dNTP. The process is continued over several hundred cycles and many images of the fluorescently-labeled cloned fragments on a flow cell are collected over the run time. In contrast, the chemistry employed on the Ion Personal Genome Machine (PGM) and Ion S5 does not make use of optical signals, thereby overcoming any optic and fluorescent dye artifacts. The PGM and S5 sequence target DNA molecules and detect each dNTP incorporated into the growing chain using ion semiconductors (i.e., a miniature pH meter). The four dNTPs are flowed sequentially across the semiconductor chip and for each dNTP incorporated into the newly synthesized strand, a proton $\left(\mathrm{H}^{+}\right)$is
released into solution (Lysholm, et al. 2011; Levy and Myers 2016). The change in pH that occurs following proton release is detected by a sensing layer of the semiconductor chip and is recorded in a flowgram. Terminator moieties are not used for this chemistry so multiple identical dNTPs (i.e., homopolymeric stretches of more than one cytosine) can be added during the same flow (Quail, et al. 2012; Levy and Myers 2016). For this chemistry, the magnitude of signal intensity (decrease in pH ) is proportional to the number of dNTPs incorporated during a single flow.


Figure 7. Sequencing methods. (A) Traditional DNA sequencing method used for decades. DNA is synthesized in the presence of fluorescently labeled ddNTPs. The differently sized fragments are separated by CE and the sequence of fluorescently labeled nucleotides is detected by a camera. (B) Single base extension. The SBE primers are extended with a fluorescently labeled ddNTP complimentary to the nucleotide in the SNP locus. The extended SBE primers are detected by CE. (C) Pyrosequencing (i.e., another method similar to the ion semiconductor chemistry). Nucleotides are added sequentially to the sequencing reaction. Incorporation of one or more nucleotide(s) to the growing strand release one or more pyrophosphate(s) that are used in secondary enzymatic reactions to generate light. The light emission is detected by a camera. (D) Semi-conductor sequencing. Nucleotides are added sequentially to the sequencing reaction. Incorporation of one or more nucleotide(s) to the growing strand release one or more hydrogen ion(s) that are detected by an ion sensor. (E) Sequencing by synthesis. DNA synthesis is performed with fluorescently labeled dNTPs with reversible 30 terminators (marked by an asterisk). Each addition of a nucleotide to the growing strand is detected by a camera. The terminator is chemically removed allowing for the next nucleotide to be incorporated. (F) Sequencing by ligation. The sequencing primer is hybridized to the target DNA and four sets of four fluorescently labeled di-base probes (all the 16 possible combinations) are added sequentially to the ligase reaction. Successful ligation of a probe to the sequencing primer is detected by a camera. The probes are cleaved (between the N and Z nucleotides) and another cycle of ligations can begin. Image borrowed from Børsting and Morling 2015.

Application of pharmacogenetic information relies on haplotype interrogation, as described for the CYP2D6 * allele nomenclature. Making haplotype inferences requires computational and/or observational phase of genetic data (Figure 8). Phased genetic data not only identify the two alleles within a genotype but also contain information about the parental origin of alleles across multiple genotypes. In Figure 8, the order of alleles within the genotype in red are changed to generate phased data; the resulting haplotypes, AABABAA and ABBAABA, were inherited from the green and blue parents, respectively. Generating phased data can be achieved computationally (e.g., algorithmic interpretation of phase) and/or observationally (e.g., long-read DNA sequencing). Computational phasing algorithms utilize dense genotype coverage (i.e., genotyping many SNPs in a relatively small region or across the entire genome) and a reference genome (Browning and Browning 2011). The 1000 Genomes Project (Karolchik, et al. 2012; 1000 Genomes Project Consortium, et al. 2015) is typically used as a phase reference due to its modest representation of global allele frequency differences. This breadth of global population coverage allows for detection of a relative majority of variation in the human population and subsequently offers a reliable base on which to infer genotype phase. Short-read DNA sequencing is limited in terms of genomic region assembly especially for duplicated and/or repeat regions (Alkan, et al. 2011). Computational phase is limited by multiple factors including sample size, degree of sample relatedness, marker density, underlying population substructure, and associated allele frequency differences (Kong, et al. 2008; Marchini, et al. 2006). Observational phase via long-read DNA sequencing, for example, provides a considerable advantage over computational phase and short read DNA sequencing because alleles at adjacent SNPs can be sequenced in the same read. Figure 9 shows this concept with representative short and long reads, using the MiSeq
and MinION as example sequencing platforms, and the SNP loci potentially captured in each read. Using short reads (Figure 9B), relatively few loci with globally frequent alternate alleles (e.g., >0.01 in 1000 Genomes Project; Figure 9A-C loci with substantial abundance of red color) can be captured in the DNA sequence. Relative to MiSeq and S5 sequencing, the longer MinION reads capture variants farther than $\sim 600$ bases from one another, such as those in large pharmacogenes. Long-read sequencing platforms, such as the MinION (Oxford Nanopore Technologies) and Single Molecule, Real Time (SMRT) sequencing (Pacific Biosciences of California, Inc.), are theoretically capable of producing continuous DNA reads resulting in comprehensive phased haplotype data (Figure 9C) (Ammar, et al. 2015; Goodwin, et al. 2016; Ip, et al. 2015; Lindberg, et al. 2016). These phased haplotypes can then be used to easily infer * allele designation and resulting metabolizer phenotype. Unfortunately, these long/continuous-read platforms are largely still under development (SMRT and MinION) and have error rates and read quality that are inappropriate for clinical diagnostics using pharmacogene targets (MinION).

## Phased v. Unphased Data



Figure 8. Examples of raw, unphased genotype data (a) and the same data after computational and/or observational phased genotype information.


Figure 9. Integrative Genomics Viewer software screenshot of the CYP2D6 locus (A) and a zoomed-in portion of exon 2 (B). The top track in each panel shows the observed 1000 Genomes Project ( 1 kGP ) SNPs, INDELs, and/or gene conversions with blue and red boxes indicating the relative frequency of the reference and alternate allele conditions in 2,504 1 kGP individuals $\left(\mathrm{N}_{\text {alleles }}=5,008\right)$. The second track contains the CYP2D6 locus $(\mathrm{A})$ or the amino acid string sequence (B). Tracks 3 and 4 contain horizontal gray bars representing short DNA reads using the MiSeq as a representative short-read chemistry; track 5 and 6 contain horizontal green bars representing long DNA reads using the MinION as a representative long-read chemistry.

In ante- and post-mortem patients, genetic characterization of the highly polymorphic CYP2D6 locus has helped make inferences regarding appropriate dosage of prescription opioid-based medications and provided insight into CoD and/or MoD. However, CYP2D6 alone is not a sole biomarker for prediction of metabolizer phenotype and findings from additional relevant loci can be especially meaningful for the healthcare, psychiatric, and forensic genetics communities. For example, individuals with normal CYP2D6 activity may experience adverse effects following drug administration due to over- or under-active transacting proteins. To date, however, there are no studies utilizing an extended opiate pathway to infer phenotypic effect with more comprehensive genetic profiles of patients. Additionally, need for haplotype phase is a large limitation to cost-effective clinical application of pharmacogenetic data. This dissertation aims to understand the relationship between genetic variation in genes encoding highly variable, metabolically-relevant proteins within the same metabolic pathway and evaluate the predictive capabilities of a pathway-driven
pharmacogenetic profile under the global hypothesis that comprehensive (full-gene) and combinatorial (multi-gene) pharmacogenetic profiles of select genes in the opiate metabolism and response pathways can be used to better predict MP of an individual. This global hypothesis was addressed using two Specific Aims: (1) define a comprehensive list of opiate metabolism and response gene polymorphisms in unexposed populations and (2) evaluate the predictive capability of polymorphisms on deceased tramadol-exposed Finns.

Specific Aim 1 has three sub-Aims: (a) assess the global genetic diversity of opiate metabolism and response genes in healthy cohorts, (b) perform full-gene haplotype analyses of CYP2D6, and (c) perform full-gene haplotype analyses of $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT. Using publically available sequence data from the 1000 Genomes Project ( $\mathrm{N} \sim 2,500$ ) and variant effect prediction algorithms, thousands of polymorphisms in the five genes of interest were characterized. The phased nature of the 1000 Genomes Project genotypes was exploited to perform haplotype analyses for all five genes. These data identified key relationships between individual SNPs and/or haplotypes in major global population groups.

Specific Aim 2 was divided into two sub-Aims: (a) predict MP of deceased Finns using CYP2D6 alone and (b) perform combinatorial modeling of MP in the same cohort of deceased Finns. Here, machine learning algorithms were used to predict MP of 208 deceased tramadolexposed Finns. The resulting predictive model will be an invaluable contribution to the personalized medicine, pharmacogenetics, and molecular autopsy communities because it can accurately predict MP categorical variables and potentially guide clinical use and prescription of the synthetic opioid agonist tramadol better than current methods of 1) single gene genetic predictions of phenotypic response and/or 2) patient response monitoring and adjusting drug dosage accordingly.

## References

Please refer to the reference list after Chapter 8 for all references cited within Chapters 1 and
8.

## PART 2

# ELUCIDATION OF THE GENETIC VARIATION OF OPIATE METABOLISM AND RESPONSE GENES IN WORLD POPULATIONS 

## CHAPTER 2

## Global Genetic Variation of Select Opiate Metabolism Genes in Self-Reported Healthy Individuals

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Frank R Wendt Gita Pathak
Antti Sajantila Ranajit Chakraborty

Bruce Budowle


#### Abstract

CYP2D6 is a pharmacogene encoding an enzyme impacting poor, intermediate, extensive, and ultrarapid phase I metabolism of many marketed drugs. The pharmacogenetics of opiate drug metabolism is particularly interesting due to the relatively high incidence of addiction and overdose. Recently, trans-acting opiate metabolism and analgesic response enzymes (UGT2B7, ABCB1, OPRM1, and COMT) have been incorporated into pharmacogenetic studies to generate more comprehensive metabolic profiles of patients. With use of massively parallel sequencing, it is possible to identify additional polymorphisms that fine tune, or redefine, previous pharmacogenetic findings, which typically rely on targeted approaches. The 1000 Genomes Project data were analyzed to describe population genetic variation and statistics for these five genes in self-reported healthy individuals in five global super- and 26 sub-populations. Findings on the variation of these genes in various populations expand baseline understanding of pharmacogenetically relevant polymorphisms for future studies of affected cohorts.


## Introduction

The cytochrome P450, family 2, subfamily D, polypeptide 6 (CYP2D6) is a clinically significant enzyme responsible for approximately $30 \%$ of phase I metabolism of approximately $25 \%$ of marketed drugs. ${ }^{1,2}$ Of particular interest is the enzyme's role in the conversion of pain medications to active metabolites, namely morphine. ${ }^{3-5}$ The highly polymorphic nature of CYP2D6 results in various metabolizer phenotypes (MP; poor [PM], intermediate [IM], extensive [EM], and ultra-rapid [UM]), ${ }^{6-8}$ typically inferred from the diplotype of CYP2D6 star $\left(^{*}\right)$ alleles (a haplotype of one or more polymorphisms along the length of the gene), ${ }^{9}$ that have been associated with lack of therapeutic response, idiosyncratic responses, or even death. ${ }^{10-12}$

Comprehensive pharmacogenetic studies have shown that single nucleotide polymorphisms (SNPs) in other opiate metabolism and pain relief pathway genes also confer variable degrees of enzyme activity. ${ }^{13-17}$ These additional genes of interest include uridine diphosphate glucuronosyltransferase, family 1, polypeptide B7 (UGT2B7), adenosine triphosphate (ATP) binding cassette, subfamily B, number 1 (ABCB1), opioid receptor mu 1 (OPRM1), and catechol-O-methyltransferase (COMT). UGT2B7 encodes an enzyme that converts morphine to morphine-6-glucuronide; these two compounds are the primary cause of the analgesic effect of opiates. $A B C B 1$ encodes p-glycoprotein (or multidrug resistance protein 1; MDR1), a membrane-associated transporter responsible for the efflux of morphine from various organs. OPRM1 encodes the primary receptor for signal transduction of the analgesic response. Lastly, COMT encodes a protein that interacts with the opioid receptor mechanism to modulate pain response through catecholamine breakdown. Polymorphisms within these genes can impact opiate metabolism by altering the performance of their protein products,
leading to non-effective treatment or clinical complications following opiate medication administration. ${ }^{14,15}$

Previous pharmacogenetic studies have focused on identifying common causal polymorphisms using genome-wide association studies (GWAS) (targeted SNP arrays and targeted massively parallel sequencing (MPS)) to determine the MP of ante- and post-mortem patients. ${ }^{17-19}$ While valuable, these methods fail to assess polymorphisms comprehensively in a target sequence on the individual and population levels. Additionally, they hinder discovery of novel polymorphisms that may provide greater insight into phenotypic variability and subsequent resequencing of target loci may be required for confirmation of allele calls. ${ }^{20}$ MPS of the full gene region may reveal additional variants, with reliable depth of coverage, which refine the current working knowledge of $C Y P 2 D 6$ * alleles, for example, those which introduce premature stop codons before the defining polymorphisms of a * allele.

Pharmacogenetic population studies often control for presence of disease phenotype while placing less emphasis on demography and population substructure as contributing factors to variable allele distribution which may confer different metabolic profiles in populations. ${ }^{10,21,22}$ Consequently, false positive associations may arise regarding the relationship between genotype and MP. ${ }^{23}$

Herein, an in silico study of the complete gene sequences of CYP2D6, UGT2B7, ABCB1, OPRM1, COMT, and their respective promoter regions was performed to identify novel SNPs, insertion/deletion (INDEL) polymorphisms, and copy number variants (CNVs), define baseline population genetic variation, and identify potential phenotypic variability in opiate metabolism and pain relief. A summary is provided of population statistics, variant effect predictions, and clustering of super- and sub-populations based on SNPs, INDELs, and

CNVs in five genes whose protein products are associated with opiate metabolism. Finally, the distribution of CYP2D6 * alleles in five super-populations and 26 sub-populations is shown which provides additional information regarding variability within the population of EMs. ${ }^{24}$ These findings serve as substantial population genetic data for healthy cohorts which may guide the pharmacogenetics community towards studies involving comprehensive genetic screening.

## Materials and Methods

Gene and promoter regions were identified using GeneCards® Human Gene Database. ${ }^{25}$ Genotype data were obtained from 2,504 unrelated healthy individuals whose sequence data were downloaded from Phase 3 of the 1000 Genomes Project using the University of California Santa Cruz (UCSC) Table Browser ${ }^{26,27}$ and the appropriate hg19 reference genome coordinates for CYP2D6, UGT2B7, ABCB1, OPRM1, COMT, and their respective promoter regions. The 1000 Genomes Project reports data with sequence depth of coverage $\geq 4 \mathrm{X}$.

Population genetic summary statistics and statistical tests were performed for five super-populations (African [AFR], Ad Mixed American [AMR], East Asian [EAS], European [EUR], and South Asian [SAS]) and 26 sub-population (Supplemental Table 1). Allele frequencies, observed and expected heterozygosity calculations, and tests for departures from Hardy-Weinberg equilibrium (HWE) and pairwise linkage disequilibrium (LD, assuming HWE) were performed using Genetic Data Analysis Software (GDA). ${ }^{28}$ Allele frequency $95 \%$ confidence intervals were estimated using the normal approximation to the binomial method. Tests for HWE departures and pairwise LD were performed for super- and sub-populations
due to the potential for loci meeting HWE expectations or pairwise loci linkage equilibrium in sub-populations but deviating from these expectations when pooled into super-populations. ${ }^{29}$ Due to the size of $A B C B 1$ and $O P R M 1$ and the number of polymorphisms within each gene, computation constraints with software memory were experienced while performing all tests for pairwise LD between these polymorphisms ( $\sim 17$ million and $\sim 23$ million pairwise comparisons for $A B C B 1$ and $O P R M 1$, respectively). Consequently, tests for pairwise LD for $A B C B 1$ and OPRM1 polymorphisms were performed between HWE-deviating loci and all other loci. Both tests are sensitive to low frequency alleles and focusing on this subset of loci for pairwise LD testing, under the assumption of HWE, could indicate if the polymorphisms are subject to some selective pressures and/or genotyping errors as a result of the relatively low coverage of 1000 Genomes Project data. ${ }^{30}$ Here we use "linkage disequilibrium block" to describe a cluster of polymorphisms with significant deviations from pairwise LD with all other polymorphisms for a gene. Ensembl Variant Predictor (Release 84, March 2016) ${ }^{31}$ and Sort Intolerant From Tolerant (SIFT) ${ }^{32-36}$ were used to determine SIFT, Polymorphism Phenotyping v2 (PolyPhen-2), ${ }^{37,38}$ and Protein Variant Effect Analyzer (PROVEAN) ${ }^{39-41}$ variant effect predictions and scores for all identified polymorphisms. Intronic positions within 1000 bases of an exon were further analyzed using Human Splicing Finder (HSF). ${ }^{42}$ Multidimensional scaling (MDS) plots and principal component analysis (PCA) plots were generated in RStudio ${ }^{\circledR} .{ }^{43}$ CYP2D6 * alleles were assigned according to the presence of causal polymorphisms associated with known phenotype ${ }^{9}$ and were used to assign activity scores and MP to each individual. ${ }^{44}$ Haplotypes producing no amino acid changes and lacking causal intronic polymorphisms were considered * 1 ; haplotypes conferring the combination of R296C and S486T amino acid changes but lacking any other amino acid change and intronic causal
polymorphisms were considered *2. Individuals possessing CYP2D6* alleles with undetermined effects on activity $(* 22, * 28$, and $* 43$, for example), or haplotypes that could not be associated with a * allele, were removed from MP analyses.

## Results

## CYP2D6

Allele frequencies for 418 polymorphic loci (402 SNPs, 15 INDELs, and one CNV) in the CYP2D6 region for five super-populations and 26 sub-populations are listed in Supplemental Table 2. The average observed heterozygosity for 26 sub-populations was $0.0341 \pm 0.102$ with a range of $0.0253 \pm 0.0836$ (CHS) to $0.0439 \pm 0.114$ (GWD) (Table 1 and Supplemental Table 3). When pooled, the average super-population observed heterozygosity was $0.0384 \pm 0.0980$ for AFR, $0.0337 \pm 0.102$ for AMR, $0.0281 \pm 0.0918$ for EAS, $0.0359 \pm$ 0.107 for EUR, and $0.0339 \pm 0.107$ for SAS (Table 1 and Supplemental Table 3). After Bonferroni correction ( $\mathrm{p}<0.000120$ ), one locus in GBR (rs35742686), one locus in EAS (rs374153932), and four loci in AFR (rs78854695, rs28371705, rs28371703, and rs376217512) significantly deviated from HWE, all of which are less than that due to chance alone (i.e., ~21) (Table 2 and Supplemental Table 4).

Table 1. Average super-population and sub-population observed $\left(\mathrm{H}_{\mathrm{o}}\right)$ and expected $\left(\mathrm{H}_{\mathrm{e}}\right)$ heterozygosities across 418 CYP2D6, 613 UGT2B7, 5,986 ABCB1, 6,831 OPRM1, and 1,007 COMT polymorphisms.

| Gene | Super-Population | Average $\mathrm{H}_{\mathrm{e}}$ | Average $\mathrm{H}_{0}$ | Sub-Population | Average $\mathrm{H}_{\mathrm{e}}$ | Average $\mathrm{H}_{0}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP2D6 | AFR | $0.0429 \pm 0.110$ | $0.0384 \pm 0.0980$ | YRI | $0.0417 \pm 0.110$ | $0.0365 \pm 0.0956$ |
|  |  |  |  | LWK | $0.0435 \pm 0.110$ | $0.0386 \pm 0.0984$ |
|  |  |  |  | GWD | $0.0433 \pm 0.111$ | $0.0440 \pm 0.114$ |
|  |  |  |  | MSL | $0.0420 \pm 0.109$ | $0.0370 \pm 0.0949$ |
|  |  |  |  | ESN | $0.0424 \pm 0.111$ | $0.0404 \pm 0.107$ |
|  |  |  |  | ASW | $0.0417 \pm 0.108$ | $0.0360 \pm 0.0956$ |
|  |  |  |  | ACB | $0.0429 \pm 0.112$ | $0.0346 \pm 0.0895$ |
|  | AMR | $0.0372 \pm 0.114$ | $0.0337 \pm 0.102$ | MXL | $0.0340 \pm 0.105$ | $0.0296 \pm 0.0892$ |
|  |  |  |  | PUR | $0.0405 \pm 0.120$ | $0.0413 \pm 0.127$ |
|  |  |  |  | CLM | $0.0386 \pm 0.115$ | $0.0317 \pm 0.0922$ |
|  |  |  |  | PEL | $0.0324 \pm 0.108$ | $0.0296 \pm 0.0983$ |
|  | EAS | $0.0308 \pm 0.102$ | $0.0281 \pm 0.0918$ | CHB | $0.0310 \pm 0.101$ | $0.0310 \pm 0.100$ |
|  |  |  |  | JPT | $0.0329 \pm 0.109$ | $0.0298 \pm 0.0995$ |
|  |  |  |  | CHS | $0.0296 \pm 0.0980$ | $0.0253 \pm 0.0836$ |
|  |  |  |  | CDX | $0.0288 \pm 0.0955$ | $0.0260 \pm 0.0843$ |
|  |  |  |  | KHV | $0.0275 \pm 0.0910$ | $0.0282 \pm 0.0955$ |
|  | EUR | $0.0400 \pm 0.121$ | $0.0359 \pm 0.107$ | CEU | $0.0410 \pm 0.122$ | $0.0353 \pm 0.104$ |
|  |  |  |  | TSI | $0.04070 \pm 0.123$ | $0.0373 \pm 0.112$ |
|  |  |  |  | FIN | $0.0376 \pm 0.1160$ | $0.0357 \pm 0.111$ |
|  |  |  |  | GBR | $0.0402 \pm 0.121$ | $0.0320 \pm 0.0949$ |
|  |  |  |  | IBS | $0.0401 \pm 0.121$ | $0.0386 \pm 0.117$ |
|  | SAS | $0.0374 \pm 0.118$ | $0.0339 \pm 0.107$ | GIH | $0.0381 \pm 0.121$ | $0.0362 \pm 0.115$ |
|  |  |  |  | PJL | $0.0340 \pm 0.111$ | $0.0333 \pm 0.108$ |
|  |  |  |  | BEB | $0.0371 \pm 0.1130$ | $0.0312 \pm 0.0949$ |
|  |  |  |  | STU | $0.0374 \pm 0.119$ | $0.0309 \pm 0.0975$ |
|  |  |  |  | ITU | $0.0381 \pm 0.121$ | $0.0374 \pm 0.119$ |
| UGT2B7 | AFR | $0.0573 \pm 0.117$ | $0.0582 \pm 0.121$ | YRI | $0.0530 \pm 0.109$ | $0.0554 \pm 0.115$ |
|  |  |  |  | LWK | $0.0610 \pm 0.125$ | $0.0668 \pm 0.140$ |
|  |  |  |  | GWD | $0.0524 \pm 0.110$ | $0.0503 \pm 0.109$ |
|  |  |  |  | MSL | $0.0495 \pm 0.103$ | $0.0492 \pm 0.105$ |
|  |  |  |  | ESN | $0.0604 \pm 0.124$ | $0.0663 \pm 0.140$ |
|  |  |  |  | ASW | $0.0605 \pm 0.125$ | $0.0681 \pm 0.143$ |
|  |  |  |  | ACB | $0.0639 \pm 0.134$ | $0.0551 \pm 0.115$ |
|  | AMR | $0.0675 \pm 0.150$ | $0.0613 \pm 0.136$ | MXL | $0.0621 \pm 0.140$ | $0.0694 \pm 0.158$ |
|  |  |  |  | PUR | $0.0723 \pm 0.161$ | $0.0684 \pm 0.151$ |
|  |  |  |  | CLM | $0.0741 \pm 0.166$ | $0.0653 \pm 0.146$ |
|  |  |  |  | PEL | $0.0448 \pm 0.105$ | $0.0420 \pm 0.104$ |
|  | EAS | $0.0611 \pm 0.142$ | $0.0644 \pm 0.151$ | CHB | $0.0646 \pm 0.150$ | $0.0847 \pm 0.200$ |
|  |  |  |  | JPT | $0.0636 \pm 0.145$ | $0.0654 \pm 0.149$ |
|  |  |  |  | CHS | $0.0605 \pm 0.141$ | $0.0698 \pm 0.165$ |
|  |  |  |  | CDX | $0.0595 \pm 0.139$ | $0.0468 \pm 0.111$ |
|  |  |  |  | KHV | $0.0570 \pm 0.133$ | $0.0529 \pm 0.127$ |
|  | EUR | $0.0741 \pm 0.168$ | $0.0777 \pm 0.177$ | CEU | $0.0738 \pm 0.169$ | $0.0836 \pm 0.193$ |
|  |  |  |  | TSI | $0.0745 \pm 0.167$ | $0.0834 \pm 0.189$ |
|  |  |  |  | FIN | $0.0744 \pm 0.168$ | $0.0665 \pm 0.150$ |
|  |  |  |  | GBR | $0.0726 \pm 0.167$ | $0.0725 \pm 0.168$ |
|  |  |  |  | IBS | $0.0746 \pm 0.168$ | $0.0814 \pm 0.184$ |
|  | SAS | $0.0720 \pm 0.164$ | $0.0740 \pm 0.170$ | GIH | $0.0727 \pm 0.167$ | $0.0744 \pm 0.172$ |
|  |  |  |  | PJL | $0.0738 \pm 0.165$ | $0.0730 \pm 0.165$ |
|  |  |  |  | BEB | $0.0701 \pm 0.159$ | $0.0731 \pm 0.167$ |
|  |  |  |  | STU | $0.0719 \pm 0.165$ | $0.0780 \pm 0.181$ |
|  |  |  |  | ITU | $0.0713 \pm 0.164$ | $0.0713 \pm 0.166$ |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of
African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

Table 1 (continued). Average super-population and sub-population observed $\left(\mathrm{H}_{\mathrm{o}}\right)$ and expected $\left(\mathrm{H}_{\mathrm{e}}\right)$ heterozygosities across 418 CYP2D6, 613 UGT2B7, 5,986 ABCB1, 6,831 OPRM1, and 1,007 COMT polymorphisms.

| Gene | Super-Population | Average $\mathrm{H}_{\mathrm{e}}$ | Average $\mathbf{H}_{0}$ | Sub-Population | Average $\mathrm{H}_{\mathrm{e}}$ | Average $\mathrm{H}_{0}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ABCB1 | AFR | $0.0295 \pm 0.0872$ | $0.0294 \pm 0.0873$ | YRI | $0.0288 \pm 0.0884$ | $0.0287 \pm 0.0885$ |
|  |  |  |  | LWK | $0.0309 \pm 0.0909$ | $0.0300 \pm 0.0880$ |
|  |  |  |  | GWD | $0.0283 \pm 0.0860$ | $0.0296 \pm 0.0914$ |
|  |  |  |  | MSL | $0.0303 \pm 0.0875$ | $0.0295 \pm 0.0855$ |
|  |  |  |  | ESN | $0.0302 \pm 0.0895$ | $0.0300 \pm 0.0903$ |
|  |  |  |  | ASW | $0.0279 \pm 0.0847$ | $0.0277 \pm 0.0853$ |
|  |  |  |  | ACB | $0.0294 \pm 0.0877$ | $0.0297 \pm 0.0893$ |
|  | AMR | $0.0209 \pm 0.0771$ | $0.0209 \pm 0.0781$ | MXL | $0.0202 \pm 0.0783$ | $0.0194 \pm 0.0775$ |
|  |  |  |  | PUR | $0.0209 \pm 0.0763$ | $0.0219 \pm 0.0812$ |
|  |  |  |  | CLM | $0.0215 \pm 0.0779$ | $0.0212 \pm 0.0767$ |
|  |  |  |  | PEL | $0.0199 \pm 0.0780$ | $0.0205 \pm 0.0821$ |
|  | EAS | $0.0186 \pm 0.0758$ | $0.0184 \pm 0.0751$ | CHB | $0.0177 \pm 0.0733$ | $0.0171 \pm 0.0711$ |
|  |  |  |  | JPT | $0.0193 \pm 0.0775$ | $0.0196 \pm 0.0795$ |
|  |  |  |  | CHS | $0.0192 \pm 0.0779$ | $0.0191 \pm 0.0762$ |
|  |  |  |  | CDX | $0.0177 \pm 0.0747$ | $0.0182 \pm 0.0789$ |
|  |  |  |  | KHV | $0.0188 \pm 0.0769$ | $0.0178 \pm 0.0735$ |
|  | EUR | $0.0189 \pm 0.0759$ | $0.0192 \pm 0.0780$ | CEU | $0.0185 \pm 0.0757$ | $0.0193 \pm 0.0807$ |
|  |  |  |  | TSI | $0.0195 \pm 0.0771$ | $0.0186 \pm 0.0738$ |
|  |  |  |  | FIN | $0.0184 \pm 0.0753$ | $0.0188 \pm 0.0785$ |
|  |  |  |  | GBR | $0.0182 \pm 0.0762$ | $0.0191 \pm 0.0801$ |
|  |  |  |  | IBS | $0.0193 \pm 0.0778$ | $0.0201 \pm 0.0817$ |
|  | SAS | $0.0174 \pm 0.0688$ | $0.0173 \pm 0.0678$ | GIH | $0.0175 \pm 0.0706$ | $0.0169 \pm 0.0666$ |
|  |  |  |  | PJL | $0.0185 \pm 0.0724$ | $0.0185 \pm 0.0723$ |
|  |  |  |  | BEB | $0.0170 \pm 0.0677$ | $0.0175 \pm 0.0695$ |
|  |  |  |  | STU | $0.0165 \pm 0.0658$ | $0.0159 \pm 0.0631$ |
|  |  |  |  | ITU | $0.0175 \pm 0.0707$ | $0.0174 \pm 0.0713$ |
| OPRMI | AFR | $0.0405 \pm 0.101$ | $0.0407 \pm 0.102$ | YRI | $0.0408 \pm 0.104$ | $0.0413 \pm 0.106$ |
|  |  |  |  | LWK | $0.0412 \pm 0.104$ | $0.04100 \pm 0.102$ |
|  |  |  |  | GWD | $0.0392 \pm 0.101$ | $0.0399 \pm 0.105$ |
|  |  |  |  | MSL | $0.0380 \pm 0.0968$ | $0.0384 \pm 0.0983$ |
|  |  |  |  | ESN | $0.0430 \pm 0.108$ | $0.0425 \pm 0.107$ |
|  |  |  |  | ASW | $0.0390 \pm 0.100$ | $0.0414 \pm 0.109$ |
|  |  |  |  | ACB | $0.0396 \pm 0.100$ | $0.0404 \pm 0.103$ |
|  | AMR | $0.0299 \pm 0.0949$ | $0.0291 \pm 0.0923$ | MXL | $0.0302 \pm 0.0982$ | $0.0327 \pm 0.108$ |
|  |  |  |  | PUR | $0.0313 \pm 0.0953$ | $0.0307 \pm 0.0945$ |
|  |  |  |  | CLM | $0.0304 \pm 0.0954$ | $0.0309 \pm 0.0983$ |
|  |  |  |  | PEL | $0.0244 \pm 0.0852$ | $0.0225 \pm 0.0778$ |
|  | EAS | $0.0225 \pm 0.0822$ | $0.0228 \pm 0.0835$ | CHB | $0.0232 \pm 0.083$ | $0.0235 \pm 0.0844$ |
|  |  |  |  | JPT | $0.0206 \pm 0.0810$ | $0.0210 \pm 0.0824$ |
|  |  |  |  | CHS | $0.0235 \pm 0.0834$ | $0.0241 \pm 0.0858$ |
|  |  |  |  | CDX | $0.0223 \pm 0.0835$ | $0.0228 \pm 0.0873$ |
|  |  |  |  | KHV | $0.0226 \pm 0.0829$ | $0.0226 \pm 0.0830$ |
|  | EUR | $0.0299 \pm 0.0962$ | $0.0302 \pm 0.0980$ | CEU | $0.0304 \pm 0.0984$ | $0.0302 \pm 0.0987$ |
|  |  |  |  | TSI | $0.0290 \pm 0.0939$ | $0.0293 \pm 0.0977$ |
|  |  |  |  | FIN | $0.0299 \pm 0.0967$ | $0.0315 \pm 0.103$ |
|  |  |  |  | GBR | $0.0297 \pm 0.0960$ | $0.0292 \pm 0.0957$ |
|  |  |  |  | IBS | $0.0304 \pm 0.0981$ | $0.0309 \pm 0.0994$ |
|  | SAS | $0.0259 \pm 0.0881$ | $0.0258 \pm 0.0888$ | GIH | $0.0266 \pm 0.0897$ | $0.0265 \pm 0.0901$ |
|  |  |  |  | PJL | $0.0256 \pm 0.0880$ | $0.0264 \pm 0.0924$ |
|  |  |  |  | BEB | $0.0250 \pm 0.0860$ | $0.0245 \pm 0.0851$ |
|  |  |  |  | STU | $0.0263 \pm 0.0897$ | $0.0267 \pm 0.0916$ |
|  |  |  |  | ITU | $0.0254 \pm 0.0887$ | $0.0248 \pm 0.0883$ |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

Table 1 (continued). Average super-population and sub-population observed $\left(\mathrm{H}_{0}\right)$ and expected $\left(\mathrm{H}_{\mathrm{e}}\right)$ heterozygosities across 418 CYP2D6, 613 UGT2B7, 5,986 ABCB1, 6,831 OPRM1, and 1,007 COMT polymorphisms.

| Gene | Super-Population | Average $\mathrm{H}_{\text {e }}$ | Average $\mathrm{H}_{0}$ | Sub-Population | Average $\mathbf{H}_{\text {e }}$ | Average $\mathrm{H}_{0}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| COMT | AFR | $0.0489 \pm 0.118$ | $0.049 \pm 0.118$ | YRI | $0.0479 \pm 0.118$ | $0.0467 \pm 0.114$ |
|  |  |  |  | LWK | $0.0493 \pm 0.118$ | $0.0479 \pm 0.114$ |
|  |  |  |  | GWD | $0.0498 \pm 0.121$ | $0.0520 \pm 0.128$ |
|  |  |  |  | MSL | $0.0484 \pm 0.117$ | $0.0473 \pm 0.114$ |
|  |  |  |  | ESN | $0.0474 \pm 0.117$ | $0.0514 \pm 0.131$ |
|  |  |  |  | ASW | $0.0503 \pm 0.120$ | $0.0498 \pm 0.120$ |
|  |  |  |  | ACB | $0.0493 \pm 0.120$ | $0.0481 \pm 0.117$ |
|  | AMR | $0.0453 \pm 0.123$ | $0.0442 \pm 0.121$ | MXL | $0.0442 \pm 0.121$ | $0.0462 \pm 0.128$ |
|  |  |  |  | PUR | $0.0466 \pm 0.125$ | $0.0445 \pm 0.120$ |
|  |  |  |  | CLM | $0.0461 \pm 0.124$ | $0.0472 \pm 0.127$ |
|  |  |  |  | PEL | $0.0372 \pm 0.111$ | $0.0392 \pm 0.123$ |
|  | EAS | $0.0429 \pm 0.124$ | $0.0425 \pm 0.122$ | CHB | $0.0442 \pm 0.125$ | $0.0423 \pm 0.120$ |
|  |  |  |  | JPT | $0.0442 \pm 0.124$ | $0.0466 \pm 0.131$ |
|  |  |  |  | CHS | $0.0411 \pm 0.123$ | $0.0420 \pm 0.126$ |
|  |  |  |  | CDX | $0.0423 \pm 0.123$ | $0.0392 \pm 0.115$ |
|  |  |  |  | KHV | $0.0424 \pm 0.124$ | $0.0418 \pm 0.123$ |
|  | EUR | $0.0435 \pm 0.122$ | $0.0443 \pm 0.125$ | CEU | $0.0435 \pm 0.123$ | $0.0458 \pm 0.130$ |
|  |  |  |  | TSI | $0.0441 \pm 0.125$ | $0.0467 \pm 0.133$ |
|  |  |  |  | FIN | $0.0414 \pm 0.115$ | $0.0401 \pm 0.112$ |
|  |  |  |  | GBR | $0.0437 \pm 0.124$ | $0.0436 \pm 0.124$ |
|  |  |  |  | IBS | $0.0428 \pm 0.122$ | $0.0451 \pm 0.129$ |
|  | SAS | $0.0456 \pm 0.123$ | $0.0437 \pm 0.118$ | GIH | $0.0463 \pm 0.125$ | $0.0460 \pm 0.124$ |
|  |  |  |  | PJL | $0.0455 \pm 0.124$ | $0.0446 \pm 0.123$ |
|  |  |  |  | BEB | $0.0448 \pm 0.123$ | $0.0404 \pm 0.111$ |
|  |  |  |  | STU | $0.0459 \pm 0.124$ | $0.0417 \pm 0.112$ |
|  |  |  |  | ITU | $0.0444 \pm 0.121$ | $0.0452 \pm 0.126$ |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

Table 2. Number of loci that deviated from Hardy-Weinberg Equilibrium (HWE) expectations and the number of pairwise loci comparisons that exhibited linkage disequilibrium (LD) for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT polymorphisms in five super-populations and 26 sub-populations. Bonferroni corrected HWE p-values were $0.000120,8.16 \times 10^{-5}, 8.35$ $\times 10^{-6}, 7.32 \times 10^{-6}$, and $4.96 \times 10^{-5}$ for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT, respectively; Bonferroni corrected pairwise LD p-values were $5.34 \times 10^{-7}, 2.67 \times 10^{-7}, 5.50 \mathrm{x}$ $10^{-8}, 2.24 \times 10^{-8}$ and $9.87 \times 10^{-8}$ for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT, respectively.

| Gene | Super-Population | Significant HWE Deviations | Significant LDs | Sub-Population | Significant HWE Deviations | Significant LDs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CYP2D6 | AFR | 4 | 3,693 | YRI | 0 | 516 |
|  |  |  |  | LWK | 0 | 500 |
|  |  |  |  | GWD | 0 | 449 |
|  |  |  |  | MSL | 0 | 452 |
|  |  |  |  | ESN | 0 | 422 |
|  |  |  |  | ASW | 0 | 331 |
|  |  |  |  | ACB | 0 | 634 |
|  | AMR | 0 | 799 | MXL | 0 | 383 |
|  |  |  |  | PUR | 0 | 560 |
|  |  |  |  | CLM | 0 | 504 |
|  |  |  |  | PEL | 0 | 380 |
|  | EAS | 1 | 1,048 | CHB | 0 | 438 |
|  |  |  |  | JPT | 0 | 385 |
|  |  |  |  | CHS | 0 | 455 |
|  |  |  |  | CDX | 0 | 425 |
|  |  |  |  | KHV | 0 | 721 |
|  | EUR | 0 | 1,031 | CEU | 0 | 595 |
|  |  |  |  | TSI | 0 | 494 |
|  |  |  |  | FIN | 0 | 387 |
|  |  |  |  | GBR | 1 | 575 |
|  |  |  |  | IBS | 0 | 402 |
|  | SAS | 0 | 933 | GIH | 0 | 402 |
|  |  |  |  | PJL | 0 | 443 |
|  |  |  |  | BEB | 0 | 472 |
|  |  |  |  | STU | 0 | 512 |
|  |  |  |  | ITU | 0 | 393 |
| UGT2B7 | AFR | 4 | 7,728 | YRI | 2 | 4,403 |
|  |  |  |  | LWK | 0 | 3,643 |
|  |  |  |  | GWD | 2 | 4,271 |
|  |  |  |  | MSL | 1 | 4,053 |
|  |  |  |  | ESN | 2 | 4,711 |
|  |  |  |  | ASW | 0 | 2,671 |
|  |  |  |  | ACB | 0 | 3,546 |
|  | AMR | 3 | 7,282 | MXL | 0 | 2,917 |
|  |  |  |  | PUR | 0 | 3,526 |
|  |  |  |  | CLM | 0 | 3,731 |
|  |  |  |  | PEL | 1 | 3,160 |
|  | EAS | 2 | 5,308 | CHB | 36 | 24,147 |
|  |  |  |  | JPT | 1 | 3,965 |
|  |  |  |  | CHS | 2 | 4,500 |
|  |  |  |  | CDX | 1 | 4,174 |
|  |  |  |  | KHV | 1 | 4,313 |
|  | EUR | 3 | 6,295 | CEU | 1 | 4,153 |
|  |  |  |  | TSI | 0 | 3,793 |
|  |  |  |  | FIN | 0 | 4,332 |
|  |  |  |  | GBR | 0 | 3,743 |
|  |  |  |  | IBS | 1 | 4,159 |
|  | SAS | 3 | 6,574 | GIH | 0 | 3,405 |
|  |  |  |  | PJL | 2 | 3,968 |
|  |  |  |  | BEB | 1 | 3,542 |
|  |  |  |  | STU | 1 | 3,962 |
|  |  |  |  | ITU | 3 | 4,959 |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

Table 2 (continued). Number of loci that deviated from Hardy-Weinberg Equilibrium (HWE) expectations and the number of pairwise loci comparisons that exhibited linkage disequilibrium (LD) for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT polymorphisms in five super-populations and 26 sub-populations. Bonferroni corrected HWE p-values were $0.000120,8.16 \times 10^{-5}, 8.35 \times 10^{-6}, 7.32 \times 10^{-6}$, and $4.96 \times 10^{-5}$ for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT, respectively; Bonferroni corrected pairwise LD p-values were $5.34 \times 10^{-}$ ${ }^{7}, 2.67 \times 10^{-7}, 5.50 \times 10^{-8}, 2.24 \times 10^{-8}$ and $9.87 \times 10^{-8}$ for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT, respectively.

| Gene | Super-Population | Significant HWEDeviations | Significant LDs | Sub-Population | Significant HWE Deviations | Significant LDs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ABCB1 | AFR | 9 | 72,978 | YRI | 0 | 11,405 |
|  |  |  |  | LWK | 0 | 4,972 |
|  |  |  |  | GWD | 1 | 12,227 |
|  |  |  |  | MSL | 2 | 14,988 |
|  |  |  |  | ESN | 1 | 12,071 |
|  |  |  |  | ASW | 0 | 2,947 |
|  |  |  |  | ACB | 1 | 13,847 |
|  | AMR | 2 | 31,011 | MXL | 0 | 7,170 |
|  |  |  |  | PUR | 1 | 9,362 |
|  |  |  |  | CLM | 1 | 11,249 |
|  |  |  |  | PEL | 0 | 5,597 |
|  | EAS | 5 | 37,802 | CHB | 2 | 15,053 |
|  |  |  |  | JPT | 0 | 5,892 |
|  |  |  |  | CHS | 2 | 15,271 |
|  |  |  |  | CDX | 0 | $6,908$ |
|  |  |  |  | KHV | 1 | 9,580 |
|  | EUR | 2 | 26,637 | CEU | 2 | 10,442 |
|  |  |  |  | TSI | 0 | 9,939 |
|  |  |  |  | FIN | 0 | 3,123 |
|  |  |  |  | GBR | 1 | 8,771 |
|  |  |  |  | IBS | 1 | 9,135 |
|  | SAS | 3 | 25,566 | GIH | 1 | 8,190 |
|  |  |  |  | PJL | 1 | 9,611 |
|  |  |  |  | BEB | 1 | 8,979 |
|  |  |  |  | STU | 1 | 10,653 |
|  |  |  |  | ITU | 1 | 9,323 |
| OPRM1 | AFR | 12 | 172,560 | YRI | 2 | 36,581 |
|  |  |  |  | LWK | 1 | 27,603 |
|  |  |  |  | GWD | 4 | 47,005 |
|  |  |  |  | MSL | 2 | 33,978 |
|  |  |  |  | ESN | 0 | 24,996 |
|  |  |  |  | ASW | 0 | 11,928 |
|  |  |  |  | ACB | 1 | 18,034 |
|  | AMR | 5 | 92,744 | MXL | 2 | 30,805 |
|  |  |  |  | PUR | 1 | 31,564 |
|  |  |  |  | CLM | 2 | 36,436 |
|  |  |  |  | PEL | 0 | 60,103 |
|  | EAS | 5 | 62,824 | CHB | 2 | 33,915 |
|  |  |  |  | JPT | 4 | 38,296 |
|  |  |  |  | CHS | 2 | 32,577 |
|  |  |  |  | CDX | 2 | 23,930 |
|  |  |  |  | KHV | 5 | 42,291 |
|  | EUR | 6 | 76,181 | CEU | 3 | 36,491 |
|  |  |  |  | TSI | 2 | 32,190 |
|  |  |  |  | FIN | 1 | 33,169 |
|  |  |  |  | GBR | 4 | 37,849 |
|  |  |  |  | IBS | 1 | 22,631 |
|  | SAS | 5 | 77,803 | GIH | 1 | 30,707 |
|  |  |  |  | PJL | 4 | 41,472 |
|  |  |  |  | BEB | 2 | 23,612 |
|  |  |  |  | STU | 4 | 44,452 |
|  |  |  |  | ITU | 3 | 33,269 |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

Table 2 (continued). Number of loci that deviated from Hardy-Weinberg Equilibrium (HWE) expectations and the number of pairwise loci comparisons that exhibited linkage disequilibrium (LD) for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT polymorphisms in five super-populations and 26 sub-populations. Bonferroni corrected HWE p-values were $0.000120,8.16 \times 10^{-5}, 8.35 \times 10^{-6}, 7.32 \times 10^{-6}$, and $4.96 \times 10^{-5}$ for $C Y P 2 D 6, U G T 2 B 7, A B C B 1$, $O P R M 1$, and COMT, respectively; Bonferroni corrected pairwise LD p-values were $5.34 \times 10^{-}$ ${ }^{7}, 2.67 \times 10^{-7}, 5.50 \times 10^{-8}, 2.24 \times 10^{-8}$ and $9.87 \times 10^{-8}$ for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT, respectively.

| Gene | Super-Population | Significant HWE Deviations | Significant LDs | Sub-Population | Significant HWE Deviations | Significant LDs |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| COMT | AFR | 1 | 7,362 | YRI | 0 | 1,421 |
|  |  |  |  | LWK | 0 | 1,428 |
|  |  |  |  | GWD | 0 | 1,252 |
|  |  |  |  | MSL | 0 | 1,003 |
|  |  |  |  | ESN | 2 | 2,492 |
|  |  |  |  | ASW | 0 | 772 |
|  |  |  |  | ACB | 0 | 1,132 |
|  | AMR | 2 | 7,004 | MXL | 0 | 1,196 |
|  |  |  |  | PUR | 0 | 2,068 |
|  |  |  |  | CLM | 2 | 1,669 |
|  |  |  |  | PEL | 0 | 4,661 |
|  | EAS | 2 | 6,712 | CHB | 0 | 2,396 |
|  |  |  |  | JPT | 0 | 1,940 |
|  |  |  |  | CHS | 0 | 1,777 |
|  |  |  |  | CDX | 0 | 1,890 |
|  |  |  |  | KHV | 1 | 3,079 |
|  | EUR | 3 | 7,835 | CEU | 1 | 2,229 |
|  |  |  |  | TSI | 0 | 1,685 |
|  |  |  |  | FIN | 2 | 2,123 |
|  |  |  |  | GBR | 0 | 2,162 |
|  |  |  |  | IBS | 0 | 2,391 |
|  | SAS | 2 | 7,502 | GIH | 0 | 2,202 |
|  |  |  |  | PJL | 0 | 1,870 |
|  |  |  |  | BEB | 0 | 3,969 |
|  |  |  |  | STU | 3 | 5,326 |
|  |  |  |  | ITU | 0 | 1,874 |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

After Bonferroni correction, sub-populations exhibited an average of $470 \pm 90$ significant pairwise LDs with a range of 331 (ASW) to 721 (KHV) significant pairwise LDs and 3,693 AFR, 799 AMR, 1,048 EAS, 1,031 EUR, and 933 SAS significant pairwise LDs were observed $\left(\mathrm{p}<5.74 \times 10^{-7}\right)$, all of which are less than that due to chance alone $(\sim 4,358$ pairwise comparisons) (Table 2 and Supplemental Figure 1). LD heat-maps of five super-
populations (Supplemental Figure 2) show a cluster of six to seven polymorphisms (rs29001678 [AMR, EUR, SAS only], rs1081000, rs28695233, rs75276289, rs76312385, rs74644586, and rs1080996), which appear to form an LD block. There were an average of 44 $\pm 14$ significant pairwise LDs between these seven polymorphisms and others within the gene, with a range of 33 (AMR) to 71 (AFR) significant pairwise LDs. This group of polymorphisms is found within CYP2D6 intron 1 (hg19 positions 42526524-42526573) and do not alter CYP2D6 function; however, rs1080995, rs74644586, and rs76312385 are part of the CYP2D6*21A haplotype and may be observed in any CYP2D6* allele with an intron 1 gene conversion with CYP2D7 (CYP2D6*11, *14B, *21B, *63, *73, *84, *88, *98, *102, *103, *104, and *105). ${ }^{9}$

MDS plots (Figure 1) were created using CYP2D6 polymorphism pairwise genetic distances between super-populations and within super-populations (between sub-populations). There was substantial separation of the AFR and EAS populations from the cluster of AMR, EUR, and SAS populations while sub-population clustering is quite diverse within each superpopulation.


Figure 1. Multidimensional scaling plots of CYP2D6 polymorphism pairwise genetic distances of five super-populations and 26 sub-populations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red " $X$ ", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.


Figure 1 (continued). Multidimensional scaling plots of CYP2D6 polymorphism pairwise genetic distances of five super-populations and 26 sub-populations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red "X", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.

Variant effect prediction for 418 CYP2D6 polymorphisms was performed using SIFT, PolyPhen-2, and PROVEAN (Table 3 and Supplemental Table 5). ${ }^{32-41}$ Individual polymorphisms were assigned to one of five categories based on their SIFT, PolyPhen-2, and PROVEAN scores: tolerated with no discrepancies (predictions are concordant), discrepancies but most likely tolerated (predictions are discordant but favor tolerance), discrepancies but most likely damaging (predictions are discordant but favor intolerance), damaging with no discrepancies (predictions are concordant), and conflicting results (only two scores are reported and their predictions are discordant). Summaries of their frequencies and distribution
across each gene are shown in Table 3 and Figure 2a, respectively. Due to the potential for multiple alternate alleles at the 54 damaging, or most likely damaging, polymorphisms (locus rs1135830, for example, can produce a non-synonymous amino acid change or a premature stop codon), 47 single amino acid changes, four premature stop codons, two frame-shift mutations, one copy number variant, one in-frame insertion, and one in-frame deletion mutations would arise. $50 \%$ (80/160) of the intronic and/or splice-associated polymorphisms were scored by HSF (Figure 2a and Supplemental Table 5). Seven of these loci (rs5030656, rs192358451, rs377504871, rs78854695, rs267608282, rs28371702, and rs267608275) were predicted to alter, or most likely alter, splicing of the gene. The locus rs28371702 is considered part of the haplotype for 35 * alleles although it has not been reported as functionally relevant. ${ }^{9}$ The remaining six polymorphisms have not been reported as part of a recognized * allele. Interestingly, the four intronic polymorphisms that are recognized by The Human Cytochrome p450 Allele Nomenclature Database ${ }^{9}$ for causing splice-defects (883G>C [rs201377835], $1846 \mathrm{G}>\mathrm{A}$ [rs3892097], 2950G>C [no rs number; invariable according to 1000 Genomes Project], and 2988G>A [rs28371725]) were either not scored by HSF or not considered variable sites in the 1000 Genomes Project and so genotypes were not exported from the UCSC Table Browser.

Table 3. Qualitative prediction of variant effect, average prediction scores, and distribution of qualitative overall polymorphism effect categories for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT and promoter regions. Note that not all polymorphisms were assigned a score by each variant effect algorithm so the total counts for each algorithm may not equal the total of the other algorithms and may be different than the total number of polymorphisms for each gene ( N ).




Figure 2. Qualitative summary of variant effect predictions. Each grey box represents a single gene: CYP2D6 (a), UGT2B7 (b), ABCB1 (c), OPRM1 (d), and COMT (e); the top vertical bars of each gene represent exonic polymorphisms scored by Sort Intolerant From Tolerant (SIFT), PolyPhen-2, and/or PROVEAN, the bottom bars represent intronic and splice-associated polymorphisms within 1,000 bases of an exon that were scored by Human Splicing Finder (HSF), and black lines spanning both sections represent large unscored intronic regions that were removed; CYP2D6 (a) and UGT2B7 (b) are to scale while ABCB1 (c), OPRM1 (d), and COMT (e) have large intronic sequences (vertical black lines) removed; hg19 reference genome coordinates are provided.


Figure 2 (continued). Qualitative summary of variant effect predictions. Each grey box represents a single gene: CYP2D6 (a), UGT2B7 (b), ABCB1 (c), OPRM1 (d), and COMT (e); the top vertical bars of each gene represent exonic polymorphisms scored by Sort Intolerant From Tolerant (SIFT), PolyPhen-2, and/or PROVEAN, the bottom bars represent intronic and splice-associated polymorphisms within 1,000 bases of an exon that were scored by Human Splicing Finder (HSF), and black lines spanning both sections represent large unscored intronic regions that were removed; CYP2D6 (a) and $U G T 2 B 7$ (b) are to scale while $A B C B 1$ (c), OPRM1 (d), and COMT (e) have large intronic sequences (vertical black lines) removed; hg 19 reference genome coordinates are provided.

The Human CYP Allele Nomenclature Database ${ }^{9}$ was used to assign * alleles to each sample. 210 unique haplotypes were observed in the 1000 Genomes Project Phase 3 dataset, representing $37 *$ alleles (Supplemental Table 6). The average super-population observed and expected heterozygosities were $0.72 \pm 0.080$ and $0.78 \pm 0.091$, respectively. Using * allele assignments, CYP2D6 significantly deviated from HWE expectations after Bonferroni correction in the AFR, AMR, EAS, and SAS super-populations ( $\mathrm{p}<0.0348$ for AFR and $\mathrm{p}=$ $0.0420,0.0442$, and 0.0348 in AMR, EAS, and SAS, respectively) and seven sub-populations $(\mathrm{p}=0.000200,0.0277,0.00290,0.00510,0.0202,0.157$, and 0.423 in ASW, LWK, MSL, YRI, CLM, GBR, and STU, respectively). After Bonferroni correction ( $p=0.01$ and $p=0.0019$ for
super- and sub-populations, respectively), the AFR super-population ( $\mathrm{p}<0.01$ ) and ASW ( $\mathrm{p}=$ 0.000200 ) significantly deviated from HWE expectations. Of the 210 observed haplotypes, only $14(6.67 \%)$ are identical to those reported in the Human CYP Allele Nomenclature Table. Though not reported in the reference table, $84.8 \%$ of the remaining haplotypes could be associated with a * allele based on the presence of causal polymorphisms, however, 18 of them could not. These haplotypes represent $0.499 \%(25 / 5008)$ of the total 1000 Genomes Project haplotypes and contain combinations of functionally relevant amino acid changes (Supplemental Table 6).

MP was assigned according to Gaedigk, et al. $2008^{44}$ (Table 4). A chi-squared goodness-of-fit test indicated no significant differences between observed MP frequencies of 1000 Genomes Project super-population data and theoretical predictions ( $\mathrm{p}=0.99$ ), previously reported values for general United States major population groups $(\mathrm{p}=0.54),{ }^{45}$ and world populations (African, American, East Asian, European, and South Central Asian) $(\mathrm{p}=0.99) .{ }^{46}$

Table 4. CYP2D6 metabolizer status counts and frequencies in five super-populations (bolded) and 26 sub-populations based on available 1000 Genomes Phase 3 causative SNP genotype data. The number of individuals in each population is indicated in parentheses; "Undetermined" metabolizer phenotype individuals contain at least one CYP2D6* allele with unknown effect on enzyme activity.

| Population | Poor |  | Intermediate |  | Extensive |  | Ultrarapid |  | Undetermined |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Count | Frequency | Count | Frequency | Count | Frequency | Count | Frequency | Count | Frequency |
| AFR (661) | 9 | 0.0136 | 35 | 0.053 | 564 | 0.853 | 0 | 0 | 53 | 0.0802 |
| ACB (96) | 2 | 0.0208 | 6 | 0.0625 | 82 | 0.8542 | 0 | 0 | 6 | 0.0625 |
| GWD (113) | 1 | 0.00885 | 2 | 0.0177 | 103 | 0.912 | 0 | 0 | 7 | 0.0619 |
| ESN (99) | 1 | 0.0101 | 11 | 0.111 | 79 | 0.798 | 0 | 0 | 8 | 0.0808 |
| MSL (85) | 3 | 0.0353 | 2 | 0.0235 | 70 | 0.824 | 0 | 0 | 10 | 0.118 |
| YRI (108) | 0 | 0 | 5 | 0.0463 | 97 | 0.898 | 0 | 0 | 6 | 0.0556 |
| LWK (99) | 0 | 0 | 4 | 0.0404 | 84 | 0.848 | 0 | 0 | 11 | 0.111 |
| ASW (61) | 2 | 0.0328 | 5 | 0.082 | 49 | 0.803 | 0 | 0 | 5 | 0.082 |
| AMR (347) | 10 | 0.0288 | 10 | 0.0288 | 291 | 0.839 | 0 | 0 | 36 | 0.104 |
| PUR (104) | 6 | 0.0577 | 5 | 0.0481 | 81 | 0.779 | 0 | 0 | 12 | 0.115 |
| CLM (94) | 4 | 0.0426 | 4 | 0.0426 | 74 | 0.787 | 0 | 0 | 12 | 0.128 |
| PEL (85) | 0 | 0 | 0 | 0 | 78 | 0.918 | 0 | 0 | 7 | 0.0824 |
| MXL (64) | 0 | 0 | 1 | 0.0156 | 58 | 0.906 | 0 | 0 | 5 | 0.0781 |
| EAS (504) | 0 | 0 | 13 | 0.0258 | 488 | 0.968 | 0 | 0 | 3 | 0.00595 |
| CHS (105) | 0 | 0 | 3 | 0.0286 | 100 | 0.952 | 0 | 0 | 2 | 0.019 |
| CDX (93) | 0 | 0 | 3 | 0.0323 | 89 | 0.957 | 0 | 0 | 1 | 0.0108 |
| KHV (99) | 0 | 0 | 5 | 0.0505 | 94 | 0.949 | 0 | 0 | 0 | 0 |
| CHB (103) | 0 | 0 | 2 | 0.0194 | 101 | 0.981 | 0 | 0 | 0 | 0 |
| JPT (104) | 0 | 0 | 0 | 0 | 104 | 1 | 0 | 0 | 0 | 0 |
| EUR (503) | 29 | 0.0577 | 32 | 0.0636 | 433 | 0.861 | 0 | 0 | 9 | 0.0179 |
| CEU (99) | 5 | 0.0505 | 9 | 0.0909 | 81 | 0.818 | 0 | 0 | 1 | 0.0101 |
| GBR (91) | 11 | 0.121 | 11 | 0.121 | 68 | 0.747 | 0 | 0 | 1 | 0.011 |
| IBS (107) | 3 | 0.028 | 2 | 0.0187 | 98 | 0.916 | 0 | 0 | 4 | 0.0374 |
| TSI (107) | 5 | 0.0467 | 7 | 0.0654 | 93 | 0.869 | 0 | 0 | 2 | 0.0187 |
| FIN (99) | 5 | 0.0505 | 3 | 0.0303 | 90 | 0.909 | 0 | 0 | 1 | 0.0101 |
| SAS (489) | 10 | 0.0204 | 24 | 0.0491 | 441 | 0.902 | 2 | 0.00409 | 12 | 0.0245 |
| PJL (96) | 1 | 0.0104 | 7 | 0.0729 | 87 | 0.906 | 0 | 0 | 1 | 0.0104 |
| BEB (86) | 2 | 0.0233 | 5 | 0.0581 | 76 | 0.884 | 0 | 0 | 3 | 0.0349 |
| STU (102) | 3 | 0.0294 | 4 | 0.0392 | 90 | 0.882 | 1 | 0.0098 | 4 | 0.0392 |
| ITU (102) | 3 | 0.0294 | 5 | 0.049 | 90 | 0.882 | 1 | 0.0098 | 3 | 0.0294 |
| GIH (103) | 1 | 0.00971 | 3 | 0.0291 | 98 | 0.951 | 0 | 0 | 1 | 0.00971 |

AFR: African; AMR: Ad Mixed American; EAS: East Asian; EUR: European; SAS: South Asian; ACB: African Caribbean in Barbados; ASW: American of African Ancestry in Southwest USA; BEB: Bengali from Bangladesh; CDX: Chinese Dai in Xishuangbanna, China; CEU: Utah Residence with Northern and Western Ancestry; CHB: Han Chinese in Beijing; CHS: Southern Han Chinese; CLM: Colombians from Medellin, Colombia; ESN: Esan in Nigeria; FIN: Finnish in Finland; GBR: British in England and Scotland; GIH: Gujarati Indian from Houston, Texas; GWD: Gambian in Western Divisions in Gambia; IBS: Iberian Population in Spain; ITU: Indian Telugu from the United Kingdom; JPT: Japanese in Tokyo, Japan; KHV: Kinh in Ho Chi Minh City, Vietnam; LWK: Luhya in Webuye, Kenya; MSL: Mende in Sierra Leone; MXL: Mexican Ancestry from Los Angeles, USA; PEL: Peruvians from Lima, Peru; PJL: Punjabi from Lahore, Pakistan; PUR: Puerto Ricans from Puerto Rico; STU: Sri Lankan Tamil from the United Kingdom; TSI: Toscani in Italia; YRI: Yoruba in Ibadan, Nigeria

EM individuals were used to create principal component analysis (PCA) plots by population (Figure 3). By super-population, the EM individuals display six prominent clusters with minimal overlap between AFR and EAS super-populations and considerable spread of the AMR, EUR, and SAS populations across the entire plot. PC1 and PC2 explain greater than $5 \%$ of the variance for ten and eight polymorphisms, respectively. The same clustering pattern is observed for sub-populations with little clustering observed within populations (data not shown).


| Locus | Loadpel Loadpcr ${ }^{2}$ Loadpc2 Loadpci ${ }^{2}$ |  |  |  | Functional Relevance? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| rs28371730 | 0.226 | 0.051 | 0.006 | 0 | - |
| rs1081000 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs28695233 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs75276289 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs74644586 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs1080996 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs1080995 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs76312385 | 0.225 | 0.051 | 0.002 | 0 | Intron 1 conversion with CYP2D7 |
| rs28624811 | 0.225 | 0.051 | 0.02 | 0 | - |
| rs 16947 | 0.225 | 0.05 | 0.019 | 0 | 2850C>T; C296R |
| rs4078247 | 0.091 | 0.008 | 0.272 | 0.074 | - |
| rs28588594 | 0.093 | 0.009 | 0.272 | 0.074 | - |
| rs 1065852 | 0.092 | 0.008 | 0.271 | 0.074 | 100 C T; P34S |
| rs58440431 | 0.092 | 0.008 | 0.271 | 0.073 | - |
| rs1080989 | 0.092 | 0.008 | 0.271 | 0.073 | - |
| rs2004511 | 0.092 | 0.009 | 0.271 | 0.073 | - |
| rs28371738 | 0.091 | 0.008 | 0.271 | 0.073 | - |
| rs1081003 | 0.08 | 0.006 | 0.227 | 0.051 | $1039 T>C ; F 112 \mathrm{~F}$ |

Figure 3. Principal component (PC) analysis of CYP2D6 extensive metabolizers using genotypes of 418 polymorphisms from 1000 Genomes Project Phase 3. Samples are clustered according to super-population; rs numbers are provided for those loci best explained by PC1 and PC2; functional relevance of the polymorphism is indicated in reference to The Human Cytochrome p450 Allele Nomenclature Table ${ }^{9}$ and concordance with variant effect prediction generated by SIFT, PolyPhen-2, PROVEAN, and HSF with green and red cells indicating tolerance and damage, respectively.

Allele frequencies for 613 UGT2B7 polymorphisms ( 585 SNPs and 28 INDELs), 5,986 ABCB1 polymorphisms (5,775 SNPs 210 INDELs, and one CNV), 6,831 OPRM1 polymorphisms (6,561 SNPs, 267 INDELs, two ALU element insertions, and one CNV), and 1,007 COMT polymorphisms (973 SNPs, 33 INDELs, and one CNV) in five super-populations and 26 sub-populations are listed in Supplemental Tables 7 through 10.

The average super-population and sub-population observed and expected heterozygosities are listed in Table 1. A full list of each polymorphism and respective population-specific observed and expected heterozygosities are shown in Supplemental Tables 11 through 14.

A summary of the total number of polymorphisms in each gene and population that deviated from HWE expectations is listed in Table 2. A comprehensive list of HWE p-values for each polymorphism in each population is provided in Supplemental Tables 15 through 18. After Bonferroni correction, UGT2B7 loci rs541550034 and rs57075995 (p < 8.16 X 10 ${ }^{-5}$ ), $A B C B 1$ loci rs546527793 and rs570071012 ( $\mathrm{p}<8.35 \times 10^{-6}$ ), and OPRM1 loci rs147765820, rs376391508, rs77321666, and rs111829729 (p < 7.32 X $10^{-6}$ ) deviated from HWE expectations in all five super-populations. While no COMT loci deviated from HWE expectations in the five super-populations $\left(\mathrm{p}=4.97 \times 10^{-5}\right)$, it should be noted that the loci rs138433986 and rs11912354 did deviate from HWE expectations in the AMR, EAS, EUR, and SAS populations $(\mathrm{p}=0.0009$ and 0.0009$)$. One sub-population, CHB , exhibited more deviations from HWE expectations than that due to chance alone (i.e., $\sim 20$ ).

A summary of the total number of pairwise loci comparisons that demonstrated significant LDs are listed in Table 2 and the distribution of LD p-values is shown in

Supplemental Figures 3 through 6. After Bonferroni correction, sub-populations exhibited an average of $4,683 \pm 4,004,9,489 \pm 3,368,33,303 \pm 9,716$, and $2,154 \pm 1,071$ significant LDs for $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT, respectively. Pairwise LD heat-maps of $U G T 2 B 7$, ABCB1, OPRM1, and COMT polymorphisms in five major super-populations (Supplemental Figures 7 through 10) show no substantial linkage blocks.

In contrast to CYP2D6, the individual MDS plots for $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT show substantial separation for all super-populations (Figure 4). Within superpopulations, sub-populations cluster relatively well with minimal overlap between superpopulations. Considering the entire dataset of $\sim 15,000$ polymorphisms, MDS plots of superpopulations follow the pattern observed with single-gene plots. However, sub-populations do not show any clustering within their respective super-populations.


Figure 4. Multidimensional scaling plots of UGT2B7, ABCB1, OPRM1, and COMT polymorphism pairwise genetic distances of five super-populations and 26 sub-populations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red "X", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.


Figure 4 (continued). Multidimensional scaling plots of $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT polymorphism pairwise genetic distances of five super-populations and 26 subpopulations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red "X", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.


Figure 4 (continued). Multidimensional scaling plots of UGT2B7, ABCB1, OPRM1, and COMT polymorphism pairwise genetic distances of five super-populations and 26 subpopulations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red "X", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.


Figure 4 (continued). Multidimensional scaling plots of UGT2B7, ABCB1, OPRM1, and COMT polymorphism pairwise genetic distances of five super-populations and 26 subpopulations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red "X", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.


Figure 4 (continued). Multidimensional scaling plots of $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT polymorphism pairwise genetic distances of five super-populations and 26 subpopulations based on 1000 Genome Project Phase 3 genotype data. African (AFR) populations are marked with a blue diamond, Ad Mixed American (AMR) populations are marked with a green plus sign, East Asian (EAS) populations are marked with a red "X", European (EUR) populations are marked with a purple minus sign, and South Asian (SAS) populations are marked with a solid black circle.

Variant effect prediction was performed on 613 UGT2B7, 5,986 ABCB1, 6,831 OPRM1, and 1,007 COMT polymorphisms to generate SIFT, PolyPhen-2, and PROVEAN scores (Supplemental Tables 19 through 22). ${ }^{32-41}$ A summary of the average score and frequency of each variant effect is displayed in Table 3. Of the damaging, or most likely, damaging, exonic polymorphisms in UGT2B7, ABCB1, OPRM1, and COMT, 100\% (15/15, 25/25, 17/17, and 5/5 polymorphisms in UGT2B7, ABCB1, OPRM1, and COMT, respectively) are the result of single amino acid changes. Intronic polymorphisms were analyzed further using HSF (Table 4). Those most likely to alter splicing of UGT2B7, OPRM1, and COMT account for < 5\% of the total number of polymorphisms scored by HSF. The intronic polymorphisms of $A B C B 1$ predicted to most likely, or potentially, alter splicing account for over $50 \%$ of the total (Table 4). These polymorphisms are distributed across introns one through sixteen, with very few splice-altering polymorphisms occurring after intron sixteen (Figure 2c). Additionally, one COMT polymorphism was recognized by the variant effect predictors as a frame-shift mutation (rs563298832) but was not assigned a score by the three algorithms used. Manual inspection of the locus in IGV shows the CATT deletion within intron 5 so assignment as a frame-shift mutation is incorrect. The HSF algorithm did not score this locus either. It is possible that this intronic polymorphism is damaging to the resulting protein, however, this assumption is not supported or refuted by the data presented.

## Intergenic Linkage Disequilibria

A total of 1,349 polymorphisms across all five target genes were assigned SIFT, PolyPhen-2, PROVEAN, and/or HSF scores. Tests for pairwise LD were performed on this subset of loci to address potential linkage disequilibria between polymorphisms that may alter
the activity of multiple proteins．After Bonferroni correction（ $5.50 \times 10^{-8}$ ），9，573 AFR，1，328 AMR，2，517 EAS，3，134 EUR，and 2，583 SAS significant pairwise LDs were observed between polymorphic loci of different genes（ $\mathrm{p}<0.0004$ ，Supplemental Table 23）．The number of significant pairwise LDs is less than that due to chance alone（i．e．，$\sim 45,461$ ），however，those that contain two causal polymorphisms may be clinically significant．After removal of significant pairwise LDs containing loci which deviate from HWE expectations，there were $539,12,124,282$ ，and 128 significant pairwise LDs in the AFR，AMR，EAS，EUR，and SAS populations，respectively，between polymorphic loci in different genes that are predicted to be damaging，or most likely damaging to the resulting protein（Figure 5）．Two polymorphisms are part of $82.2 \%, 98.4 \%, 46.8 \%$ ，and $85.9 \%$ of these significant pairwise LDs within AFR， EAS，EUR，and SAS，respectively（rs5885589 and rs677830）．Rs5885589 is an ABCB1 intronic polymorphism which breaks an existing splice site and activates a cryptic splice site just upstream of exon 17．Rs677830 is found within exon 4 of OPRM1 and confers glutamine 411 stop in transcript variant 1B5．${ }^{47}$ The AMR population does not have a substantial percentage of pairwise LDs associated with a single polymorphism．

| $\begin{aligned} & \text { CYP2D6 } \\ & \text { UGT2B7 } \end{aligned}$ | 25 |  |  |  |  | $\begin{aligned} & \text { CYP2D6 } \\ & \text { UGT2B7 } \end{aligned}$ | 0 |  |  |  |  | $\begin{aligned} & \text { CYP2D6 } \\ & \text { UGT2B7 } \end{aligned}$ | 0 |  |  |  |  | $\begin{aligned} & \text { CYP2D6 } \\ & \text { UGT2B7 } \end{aligned}$ | 4 |  |  |  |  | $\begin{aligned} & \text { CYP2D6 } \\ & \text { UGT2B7 } \end{aligned}$ | 0 |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ABCB1 | 330 | 24 |  |  |  | ABCB1 | 7 | 1 |  |  |  | ABCB1 | 3 | 0 |  |  |  | ABCB1 | 128 | 0 |  |  |  | ABCB1 | 17 | 0 |  |  |  |
| OPRM1 | 40 | 7 | 103 |  |  | OPRM1 | 0 | 0 | 0 |  |  | OPRM1 | 0 | 0 | 102 |  |  | OPRM1 | 14 | 0 | 112 |  |  | OPRM1 | 0 | 0 | 95 |  |  |
| COMT | 10 | 0 | 0 | 3 |  | COMT | 1 | 1 | 2 | 0 |  | COMT | 0 | 0 | 15 | 4 |  | COMT | 6 | 0 | 14 | 4 |  | COMT | 0 | 0 | 14 | 2 |  |
| AFR | $\begin{aligned} & \text { y } \\ & \stackrel{N}{N} \\ & \text { Nu } \end{aligned}$ | $\begin{aligned} & \text { N } \\ & \text { Ē } \end{aligned}$ | $\begin{aligned} & \text { O} \\ & 0 \\ & \mathbb{\infty} \\ & \hline \end{aligned}$ |  | 5 | AMR | ロ̀ N I | $\begin{aligned} & \text { M } \\ & \text { Nิ } \\ & \text { n } \end{aligned}$ | $\begin{aligned} & \text {-u } \\ & \text { © } \end{aligned}$ |  | sis | EAS | $$ | $\begin{aligned} & \text { N } \\ & \text { È } \\ & \text { B } \end{aligned}$ | －0 － － | $\begin{gathered} \text { Na } \\ \underset{\sim}{⿺} \\ 0 \end{gathered}$ | ${ }_{0}^{1}$ | EUR | Q N 气 | $\begin{aligned} & \stackrel{凶}{2} \\ & \text { E. } \\ & 3 \end{aligned}$ | $\begin{aligned} & \text { ô } \\ & 0 \\ & 0 \end{aligned}$ | $\begin{aligned} & \text { Na } \\ & \text { K } \\ & 0 \end{aligned}$ | ${ }_{0}^{1}$ | SAS | $$ | $\begin{aligned} & \text { N } \\ & \text { Nิ } \\ & 3 \end{aligned}$ | $\begin{aligned} & \text {-u } \\ & \text { © } \end{aligned}$ | çe | 5 |

Figure 5．Summary of significant pairwise linkage disequilibria between polymorphisms on different genes in five major super－populations：African（AFR），Ad Mixed American（AMR）， East Asian（EAS），European（EUR），and South Asian（SAS）．

## Discussion

Our study is limited by two factors. Firstly, the coverage requirement for the 1000 Genomes Project is $\sim 4 \mathrm{X}$, producing an inherent level of missing variants or error in the sequence data. Secondly, due to limited size in each subpopulation, some rare alleles may not be observed due to sample size. When data are generated in-house with greater sub-population samples sizes, greater coverage can be applied that will reduce the level of error and increase the chance of observing rare alleles. However, our analyses add to the population studies on pharmacogenetically interesting genes at global scale. ${ }^{48-50}$

Potential contributors to the number of significant deviations from HWE expectations that were observed for CYP2D6 and UGT2B7 polymorphisms in the ACB and CHB populations, respectively, are allele drop-out, the effects of selection, and/or population substructure. For both sub-populations, some degree of substructure has been reported. ${ }^{51-53}$ The Barbadian (ACB) population has demonstrated a higher degree of substructure relative to other ancestral African populations. ${ }^{51,52}$ The Han Chinese also show some degree of substructure attributed to northern and southern Han populations. It has been shown that the 1000 Genomes CHB population contains individuals from these Han sub-groups. ${ }^{53}$

The 1000 Genomes Project contains self-reported healthy individuals and as such, the prevalence of CYP2D6 PM, IM, and UM metabolizers may not reflect previously published datasets focusing on cohorts of affected individuals. The PCA plots of EMs explain relatively little variation ( $5.0 \%$ and $3.2 \%$, respectively, for principle components one and two). These data support previous work demonstrating some level of intra-metabolizer status variability as well as intra-sub-population variability, which is supported by MDS plot of each population.

The CYP2D6 MDS plots show separation of AFR and EAS from the cluster of AMR, EUR, and SAS, supporting previously reported clinical differences between these populations. ${ }^{54}$ Lack of tight sub-population (within super-population) clustering supports previous findings that CYP2D6 activity variation may be greater within than between superpopulations. ${ }^{55}$ For example, the sub-populations within the EAS super-population (CDX, CHB, CHS, KHV, and JPT) do not cluster tightly. The MDS plot indicates that the Chinese and Vietnamese populations (CDX, CHB, CHS, and KHV) may be different from the Japanese (JPT) population. While minimal, this Asian variability is not novel and may be clinically significant when treating patients of these ancestries. ${ }^{56}$ MDS plots of $U G T 2 B 7, A B C B 1$, OPRM1, and COMT show considerably less between super-population clustering, specifically of the SAS, EUR, and AMR populations, suggesting that differences in these genes may be somewhat associated to super-populations. MDS plots of $\sim 15,000$ polymorphisms do not show sub-population clustering with their respective super-populations. This observation may be explained by the extreme allele frequency differences between sub-populations of the same super-population. For example, the $O P R M 1$ SNP, rs66579098, has alternate allele frequencies of $0.27,0.33,0.52$, and 0.78 in the PUR, CLM, MXL, and PEL sub-populations, respectively (belonging to the AMR super-population)..$^{26,57}$

Tests for pairwise LD of damaging, or likely damaging, polymorphisms in all five genes showed association between polymorphisms from all genes. The rs677830 (OPRM1) and rs5885589 (ABCB1) account for a substantial percentage of significant pairwise LDs in the AFR, EAS, EUR, and SAS populations. These significant LDs may be clinically relevant due to the potential for multilocus interactions ${ }^{44}$. To our knowledge, rs677830 and rs5885589 have not been reported as causal polymorphisms. Interactions between these loci, or others,
may be responsible for compensation when a damaging polymorphism dramatically alters normal protein activity, as suggested by Bartošová, et al. $2015^{58}$ and Barratt, et al. $2012{ }^{59}$ with $A B C B 1$ and OPRM1 polymorphisms shown to alter protein activity in vivo.

In conclusion, baseline population summary statistics are presented on five genes involved in opiate metabolism that have been implicated in phenotypic variability leading to idiosyncratic responses in patients. This study demonstrates some genetic association between CYP2D6 and UGT2B7, ABCB1, OPRM1, and COMT that will be important for future pharmacogenetic studies and combinatorial genetic approaches for patient care.

## References

1. Ingelman-Sundberg M, Sim SC, Gomez A, Rodriguez-Antona C. Influence of cytochrome P450 polymorphisms on drug therapies: pharmacogenetic, pharmacoepigenetic and clinical aspects.Pharmacol Ther. 2007 Dec;116(3):496-526. Epub 2007 Oct 9. Review. PubMed PMID: 18001838.
2. Ingelman-Sundberg M. Genetic polymorphisms of cytochrome P450 2D6 (CYP2D6): clinical consequences, evolutionary aspects and functional diversity. Pharmacogenomics J. 2005;5(1):6-13. Review. PubMed PMID: 15492763.
3. Leppert W. CYP2D6 in the metabolism of opioids for mild to moderate pain. Pharmacology. 2011;87(5-6):274-85. doi: 10.1159/000326085. Epub 2011 Apr 15. Review. PubMed PMID: 21494059.
4. Frost J, Helland A, Nordrum IS, Slørdal L. Investigation of morphine and morphine glucuronide levels and cytochrome P450 isoenzyme 2D6 genotype in codeine-related deaths. Forensic Sci Int. 2012 Jul 10;220(1-3):6-11. doi: 10.1016/j.forsciint.2012.01.019. Epub 2012 Jan 28. PubMed PMID: 22285504.
5. Frost J, Løkken TN, Helland A, Nordrum IS, Slørdal L.Post-mortem levels and tissue distribution of codeine, codeine-6-glucuronide, norcodeine, morphine and morphine glucuronides in a series of codeine-related deaths. Forensic Sci Int. 2016 May;262:128-37. doi: 10.1016/j.forsciint.2016.02.051. Epub 2016 Mar 4. PubMed PMID: 26986973.
6. Zhou SF, Di YM, Chan E, Du YM, Chow VD, Xue CC, et al. Clinical pharmacogenetics and potential application in personalized medicine. Curr Drug Metab. 2008 Oct;9(8):73884. Review. PubMed PMID: 18855611.
7. Sistonen J, Madadi P, Ross CJ, Yazdanpanah M, Lee JW, Landsmeer ML, et al. Prediction of codeine toxicity in infants and their mothers using a novel combination of maternal genetic markers. Clin Pharmacol Ther. 2012 Apr;91(4):692-9. doi: 10.1038/clpt.2011.280. Epub 2012 Mar 7. PubMed PMID: 22398969.
8. Weber A, Szalai R, Sipeky C, Magyari L, Melegh M, Jaromi L,et al. Increased prevalence of functional minor allele variants of drug metabolizing CYP2B6 and CYP2D6 genes in Roma population samples. Pharmacol Rep. 2015 Jun;67(3):460-4. doi: 10.1016/j.pharep.2014.11.006. Epub 2014 Nov 27. PubMed PMID: 25933954.
9. The Human Cytochrome p450 Allele Nomenclature Database http://www.cypalleles.ki.se/cyp2d6.htm
10. Diatchenko L, Slade GD, Nackley AG, Bhalang K, Sigurdsson A, Belfer I, et al. Genetic basis for individual variations in pain perception and the development of a chronic pain condition. Hum Mol Genet. 2005 Jan 1;14(1):135-43. Epub 2004 Nov 10. PubMed PMID: 15537663.
11. Koren G, Cairns J, Chitayat D, Gaedigk A, Leeder SJ. Pharmacogenetics of morphine poisoning in a breastfed neonate of a codeine-prescribed mother. Lancet. 2006 Aug 19;368(9536):704. PubMed PMID: 16920476.
12. Sallee FR, DeVane CL, Ferrell RE. Fluoxetine-related death in a child with cytochrome P450 2D6 genetic deficiency. J Child Adolesc Psychopharmacol. 2000 Spring;10(1):27-34. PubMed PMID: 10755579.
13. Altar CA, Carhart JM, Allen JD, Hall-Flavin DK, Dechairo BM, Winner JG. Clinical validity: Combinatorial pharmacogenomics predicts antidepressant responses and healthcare utilizations better than single gene phenotypes. Pharmacogenomics J. 2015 Oct;15(5):443-51. doi: 10.1038/tpj.2014.85. Epub 2015 Feb 17. PubMed PMID: 25686762.
14. Lam J, Woodall KL, Solbeck P, Ross CJ, Carleton BC, Hayden MR, et al. Codeine-related deaths: The role of pharmacogenetics and drug interactions. Forensic Sci Int. 2014 Jun;239:50-6. doi: 10.1016/j.forsciint.2014.03.018. Epub 2014 Mar 26. PubMed PMID: 24747667.
15. Baber M, Chaudhry S, Kelly L, Ross C, Carleton B, Berger H, et al. The pharmacogenetics of codeine pain relief in the postpartum period. Pharmacogenomics J. 2015 Oct;15(5):4305. doi: 10.1038/tpj.2015.3. Epub 2015 Mar 10. PubMed PMID: 25752520.
16. Bastami S, Gupta A, Zackrisson AL, Ahlner J, Osman A, Uppugunduri S. Influence of UGT2B7, OPRM1 and ABCB1 gene polymorphisms on postoperative morphine consumption. Basic Clin Pharmacol Toxicol. 2014 Nov;115(5):423-31. doi: 10.1111/bcpt.12248. Epub 2014 May 19. PubMed PMID: 24703092.
17. Yuferov V, Levran O, Proudnikov D, Nielsen DA, Kreek MJ. Search for genetic markers and functional variants involved in the development of opiate and cocaine addiction and treatment. Ann N Y Acad Sci. 2010 Feb;1187:184-207. doi: 10.1111/j.17496632.2009.05275.x. Review. PubMed PMID: 20201854; PubMed Central PMCID: PMC3769182.
18. Brion M, Sobrino B, Martinez M, Blanco-Verea A, Carracedo A. Massive parallel sequencing applied to the molecular autopsy in sudden cardiac death in the young. Forensic Sci Int Genet. 2015 Sep;18:160-70. doi: 10.1016/j.fsigen.2015.07.010. Epub 2015 Jul 23. PubMed PMID: 26243589.
19. Narula N, Tester DJ, Paulmichl A, Maleszewski JJ, Ackerman MJ. Post-mortem Whole exome sequencing with gene-specific analysis for autopsy-negative sudden unexplained death in the young: a case series.Pediatr Cardiol. 2015 Apr;36(4):768-78. doi: 10.1007/s00246-014-1082-4. Epub 2014 Dec 13. PubMed PMID: 25500949.
20. Koch WH. Technology platforms for pharmacogenomic diagnostic assays. Nat Rev Drug Discov. 2004 Sep;3(9):749-61. Review. PubMed PMID: 15340385.
21. Brandl EJ, Tiwari AK, Zhou X, Deluce J, Kennedy JL, Müller DJ, et al. Influence of CYP2D6 and CYP2C19 gene variants on antidepressant response in obsessive-compulsive disorder. Pharmacogenomics J. 2014 Apr;14(2):176-81. doi: 10.1038/tpj.2013.12. Epub 2013 Apr 2. PubMed PMID: 23545896.
22. Levo A, Koski A, Ojanperä I, Vuori E, Sajantila A. Post-mortem SNP analysis of CYP2D6 gene reveals correlation between genotype and opioid drug (tramadol) metabolite ratios in blood. Forensic Sci Int. 2003 Jul 29;135(1):9-15. PubMed PMID: 12893130.
23. Rosenberg NA, Huang L, Jewett EM, Szpiech ZA, Jankovic I, Boehnke M.Genome-wide association studies in diverse populations. Nat Rev Genet. 2010 May;11(5):356-66. doi: 10.1038/nrg2760. Review. PubMed PMID: 20395969; PubMed Central PMCID: PMC3079573.
24. Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2016 Jul 7. doi: 10.1038/gim.2016.80. [Epub ahead of print] PubMed PMID: 27388693.
25. Stelzer G, Dalah I, Stein TI, Satanower Y, Rosen N, Nativ N, et al. In-silico human genomics with GeneCards. Hum Genomics. 2011 Oct;5(6):709-17. PubMed PMID: 22155609; PubMed Central PMCID: PMC3525253.
26. 1000 Genomes Project Consortium, Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, et al. A global reference for human genetic variation. Nature. 2015 Oct 1;526(7571):68-74. doi: 10.1038/nature15393. PubMed PMID: 26432245; PubMed Central PMCID: PMC4750478.
27. Karolchik D, Hinrichs AS, Kent WJ. The UCSC Genome Browser. Curr Protoc Bioinformatics. 2012 Dec;Chapter 1:Unit1.4. doi: 10.1002/0471250953.bi0104s40. PubMed PMID: 23255150.
28. Genetic Data Analysis Software. Lewis and Zaykin. 1999.
29. Wang J, Shete S. Testing departure from Hardy-Weinberg proportions. Methods Mol Biol. 2012;850:77-102. doi: 10.1007/978-1-61779-555-8_6. PubMed PMID: 22307695.
30. Teo YY, Fry AE, Clark TG, Tai ES, Seielstad M. On the usage of HWE for identifying genotyping errors. Ann Hum Genet. 2007 Sep;71(Pt 5):701-3; author reply 704. PubMed PMID: 17388941.
31. McLaren W, Pritchard B, Rios D, Chen Y, Flicek P, et al. Deriving the consequences of genomic variants with the Ensembl API and SNP Effect Predictor. Bioinformatics. 2010

Aug 15;26(16):2069-70. doi: 10.1093/bioinformatics/btq330. Epub 2010 Jun 18. PubMed PMID: 20562413; PubMed Central PMCID: PMC2916720.
32. Kumar P, Henikoff S, Ng PC. Predicting the effects of coding non-synonymous variants on protein function using the SIFT algorithm. Nat Protoc. 2009;4(7):1073-81. doi: 10.1038/nprot.2009.86. Epub 2009 Jun 25. PubMed PMID: 19561590.
33. Ng PC, Henikoff S. Predicting the effects of amino acid substitutions on protein function. Annu Rev Genomics Hum Genet. 2006;7:61-80. Review. PubMed PMID: 16824020.
34. Ng PC, Henikoff S. SIFT: Predicting amino acid changes that affect protein function. Nucleic Acids Res. 2003 Jul 1;31(13):3812-4. PubMed PMID: 12824425; PubMed Central PMCID: PMC168916.
35. Ng PC, Henikoff S. Accounting for human polymorphisms predicted to affect protein function. Genome Res. 2002 Mar;12(3):436-46. PubMed PMID: 11875032; PubMed Central PMCID: PMC155281.
36. Ng PC, Henikoff S. Predicting deleterious amino acid substitutions. Genome Res. 2001 May;11(5):863-74. PubMed PMID: 11337480; PubMed Central PMCID: PMC311071.
37. Adzhubei IA, Schmidt S, Peshkin L, Ramensky VE, Gerasimova A, Bork P, et al. A method and server for predicting damaging missense mutations. Nat Methods. 2010 Apr;7(4):248-9. doi: 10.1038/nmeth0410-248. PubMed PMID: 20354512; PubMed Central PMCID: PMC2855889.
38. Adzhubei I, Jordan DM, Sunyaev SR. Predicting functional effect of human missense mutations using PolyPhen-2. Curr Protoc Hum Genet. 2013 Jan; Chapter 7:Unit7.20. doi: 10.1002/0471142905.hg0720s76. PubMed PMID: 23315928; PubMed Central PMCID: PMC4480630.
39. Choi Y, Sims GE, Murphy S, Miller JR, Chan AP. Predicting the functional effect of amino acid substitutions and indels. PLoS One. 2012;7(10):e46688. doi: 10.1371/journal.pone.0046688. Epub 2012 Oct 8. PubMed PMID: 23056405; PubMed Central PMCID: PMC3466303.
40. Choi Y, Chan AP. PROVEAN web server: a tool to predict the functional effect of amino acid substitutions and indels. Bioinformatics. 2015 Aug 15;31(16):2745-7. doi: 10.1093/bioinformatics/btv195. Epub 2015 Apr 6. PubMed PMID: 25851949; PubMed Central PMCID: PMC4528627.
41. Choi Y (2012) A Fast Computation of Pairwise Sequence Alignment Scores Between a Protein and a Set of Single-Locus Variants of Another Protein. In Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine (BCB '12). ACM, New York, NY, USA, 414-417.
42. Desmet FO, Hamroun D, Lalande M, Collod-Béroud G, Claustres M, Béroud C. Human Splicing Finder: an online bioinformatics tool to predict splicing signals. Nucleic Acids Res. 2009 May;37(9):e67. doi: 10.1093/nar/gkp215. PubMed PMID: 19339519; PubMed Central PMCID: PMC2685110.
43. RStudio Team (2015). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.
44. Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS. The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther. 2008 Feb;83(2):234-42. Epub 2007 Oct 31. PubMed PMID: 17971818.
45. Bernard S, Neville KA, Nguyen AT, Flockhart DA. Interethnic differences in genetic polymorphisms of CYP2D6 in the U.S. population: clinical implications. Oncologist. 2006 Feb;11(2):126-35. Review. PubMed PMID: 16476833.
46. Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2016 Jul 7. doi: 10.1038/gim.2016.80. [Epub ahead of print] PubMed PMID: 27388693.
47. https://www.ncbi.nlm.nih.gov/nuccore/NM_001145286.2
48. Wilson JF, Weale ME, Smith AC, Gratrix F, Fletcher B, Thomas MG, Bradman N, Goldstein DB. Population genetic structure of variable drug response. Nat Genet. 2001 Nov;29(3):265-9. PubMed PMID: 11685208.
49. Li J, Zhang L, Zhou H, Stoneking M, Tang K. Global patterns of genetic diversity and signals of natural selection for human ADME genes. Hum Mol Genet. 2011 Feb 1;20(3):528-40. doi: 10.1093/hmg/ddq498. Epub 2010 Nov 16. PubMed PMID: 21081654.
50. Mizzi C, Dalabira E, Kumuthini J, Dzimiri N, Balogh I, Başak N, Böhm R, Borg J, Borgiani P, Bozina N, Bruckmueller H, Burzynska B, Carracedo A, Cascorbi I, Deltas C, Dolzan V, Fenech A, Grech G, Kasiulevicius V, Kádaši L, Kučinskas V, Khusnutdinova E, Loukas YL, Macek M Jr, Makukh H, Mathijssen R, Mitropoulos K, Mitropoulou C, Novelli G, Papantoni I, Pavlovic S, Saglio G, Setric J, Stojiljkovic M, Stubbs AP, Squassina A, Torres M, Turnovec M, van Schaik RH, Voskarides K, Wakil SM, Werk A, Del Zompo M, Zukic B, Katsila T, Lee MT, Motsinger-Rief A, Mc Leod HL, van der Spek PJ, Patrinos GP. A European Spectrum of Pharmacogenomic Biomarkers: Implications for Clinical Pharmacogenomics. PLoS One. 2016 Sep 16;11(9):e0162866. doi: 10.1371/journal.pone.0162866. eCollection 2016. PubMed PMID: 27636550.
51. Murray T, Beaty TH, Mathias RA, Rafaels N, Grant AV, Faruque MU, et al. African and non-African admixture components in African Americans and an African Caribbean population. Genet Epidemiol. 2010 Sep;34(6):561-8. doi: 10.1002/gepi.20512. PubMed PMID: 20717976; PubMed Central PMCID: PMC3837693.
52. Benn-Torres J, Bonilla C, Robbins CM, Waterman L, Moses TY, Hernandez W, et al. Admixture and population stratification in African Caribbean populations. Ann Hum Genet. 2008 Jan;72(Pt 1):90-8. Epub 2006 Oct 1. PubMed PMID: 17908263.
53. Xu S, Yin X, Li S, Jin W, Lou H, Yang L, Gong X, Wang H, Shen Y, Pan X, He Y, Yang Y, Wang Y, Fu W, An Y, Wang J, Tan J, Qian J, Chen X, Zhang X, Sun Y, Zhang X, Wu B, Jin L. Genomic dissection of population substructure of Han Chinese and its implication in association studies. Am J Hum Genet. 2009 Dec;85(6):762-74. doi: 10.1016/j.ajhg.2009.10.015. PubMed PMID: 19944404; PubMed Central PMCID: PMC2790582.
54. Yasuda SU, Zhang L, Huang SM. The role of ethnicity in variability in response to drugs: focus on clinical pharmacology studies. Clin Pharmacol Ther. 2008 Sep;84(3):417-23. doi: 10.1038/clpt.2008.141. Epub 2008 Jul 9. PubMed PMID: 18615002.
55. Sistonen J, Sajantila A, Lao O, Corander J, Barbujani G, Fuselli S.CYP2D6 worldwide genetic variation shows high frequency of altered activity variants and no continental structure.Pharmacogenet Genomics. 2007 Feb;17(2):93-101. PubMed PMID: 17301689.
56. Qin S, Shen L, Zhang A, Xie J, Shen W, Chen L, et al. Systematic polymorphism analysis of the CYP2D6 gene in four different geographical Han populations in mainland China. Genomics. 2008 Sep;92(3):152-8. doi: 10.1016/j.ygeno.2008.05.004. Epub 2008 Jul 15. PubMed PMID: 18632250.
57. Sulovari A, Chen YH, Hudziak JJ, Li D. Atlas of human diseases influenced by genetic variants with extreme allele frequency differences. Hum Genet. 2017 Jan;136(1):39-54. doi: 10.1007/s00439-016-1734-y. PubMed PMID: 27699474.
58. Bartošová O, Polanecký O, Perlík F, Adámek S, Slanař O. OPRM1 and ABCB1 polymorphisms and their effect on postoperative pain relief with piritramide. Physiol Res. 2015;64 Suppl 4:S521-7. PubMed PMID: 26681082.
59. Barratt DT, Coller JK, Hallinan R, Byrne A, White JM, Foster DJ, Somogyi AA. ABCB1 haplotype and OPRM1 118A \> G genotype interaction in methadone maintenance treatment pharmacogenetics. Pharmgenomics Pers Med. 2012;5:53-62. doi: 10.2147/PGPM.S29272. PubMed PMID: 23226062; PubMed Central PMCID: PMC3513228.

## Supplementary Information

Supplemental Table 1. 1000 Genomes Project population codes and descriptions for five super-populations and 26 sub-populations. ${ }^{26}$

| Super-Population (Code) | Sample Size | Population Code | Population Description | Sample Size |
| :---: | :---: | :---: | :---: | :---: |
| African (AFR) | 661 | YRI | Yoruba in Ibadan, Nigeria | 108 |
|  |  | LWK | Luhya in Webuye, Kenya | 99 |
|  |  | GWD | Gambian in Western Divisions in Gambia | 113 |
|  |  | MSL | Mende in Sierra Leone | 85 |
|  |  | ESN | Esan in Nigeria | 99 |
|  |  | ASW | American of African Ancestry in Southwest United States | 61 |
|  |  | ACB | African Caribbeans in Barbados | 96 |
| Ad Mixed <br> American (AMR) | 347 | MXL | Mexican Ancestry from Los Angeles, USA | 64 |
|  |  | PUR | Puerto Ricans from Puerto Rico | 104 |
|  |  | CLM | Colombians from Medellin, Colombia | 94 |
|  |  | PEL | Peruvians from Lima, Peru | 85 |
| East Asian (EAS) | 504 | CHB | Han Chinese in Beijing China | 103 |
|  |  | JPT | Japanese in Tokyo, Japan | 104 |
|  |  | CHS | Southern Han Chinese | 105 |
|  |  | CDX | Chinese Dai in Xishuangbanna, China | 93 |
|  |  | KHV | Kinh in Ho Chi Minh City, Vietnam | 99 |
| European (EUR) | 503 | CEU | Utah Residents (CEPH) with Northern and Western Ancestry | 99 |
|  |  | TSI | Toscani in Italia | 107 |
|  |  | FIN | Finnish in Finland | 99 |
|  |  | GBR | British in England and Scotland | 91 |
|  |  | IBS | Iberian Population in Spain | 107 |
| South Asian (SAS) | 489 | GIH | Gujarati Indian from Houston, Texas | 103 |
|  |  | PJL | Punjabi from Lahore, Pakistan | 96 |
|  |  | BEB | Bengali from Bangladesh | 86 |
|  |  | STU | Sri Lankan Tamil from the United Kingdom | 102 |
|  |  | ITU | Indian Telugu from the United Kingdom | 102 |

Supplemental Table 2. Allele frequencies and counts for CYP2D6 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Multiple alternate alleles and allele frequencies for the same locus are separated by a comma; N is equal to the number of alleles in the respective population. Supplemental Table 2 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 3. Observed and expected heterozygosities for CYP2D6 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population. Supplemental Table 3 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 4. Hardy-Weinberg equilibrium p-values for CYP2D6 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population; bolded and italicized values are
significant after Bonferroni correction ( $\mathrm{p}=0.000120$ ). Supplemental Table 4 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).


Supplemental Figure 1. Distribution of pairwise linkage disequilibrium p-values $<1$ for CYP2D6 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five major global super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Each boxplot represents a single populations; the center horizontal line represents the mean, the lower and upper boundaries of each box represent the first and third quartiles, respectively, the vertical dashed lines indicate plus/minus three times the interquartile range, and closed circles indicate outliers; $N$ is equal to the number of individuals in each population; p-values for specific pairwise loci comparisons may be shared upon request.


Supplemental Figure 2. Heat map of linkage disequilibrium p-values for CYP2D6 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations. Super-populations are separated by a diagonal red line.

Supplemental Table 5. Variant effect prediction for 418 polymorphisms in the CYP2D6 gene region. Supplemental Table 5 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 6. CYP2D6 star (*) allele frequencies ( $95 \%$ confidence interval) in five super- and 26 sub-populations. Supplemental Table 6 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 7. Allele frequencies and counts for $U G T 2 B 7$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Multiple alternate alleles for the same locus are separated by a comma; N is equal to the number of alleles in the respective population. Supplemental Table 7 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 8. Allele frequencies and counts for $A B C B 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Multiple alternate alleles for the same locus are separated by a comma; N is equal to the number of alleles in the respective population. Supplemental Table 8 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 9. Allele frequencies and counts for $O P R M 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Multiple alternate alleles for the same locus are separated by a comma; N is equal to the number of alleles in the respective population. Supplemental Table 9 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 10. Allele frequencies and counts for COMT single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Multiple alternate alleles for the same locus are separated by a comma; $N$ is equal to the number of alleles in the respective population. Supplemental Table 10 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 11. Observed and expected heterozygosities for $U G T 2 B 7$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population. Supplemental Table 11 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 12. Observed and expected heterozygosities for $A B C B 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population. Supplemental Table 12 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 13. Observed and expected heterozygosities for OPRM1 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population. Supplemental Table 13 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 14. Observed and expected heterozygosities for $C O M T$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population. Supplemental Table 14 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 15. Hardy-Weinberg equilibrium p-values for $U G T 2 B 7$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population; bolded and italicized values are significant after Bonferroni correction ( $\mathrm{p}=8.16 \mathrm{X} 10^{-5}$ ). Supplemental Table 15 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 16. Hardy-Weinberg equilibrium p-values for $A B C B 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population; bolded and italicized values are significant after Bonferroni correction ( $\mathrm{p}=8.35 \mathrm{X} 10^{-6}$ ). Supplemental Table 16 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 17. Hardy-Weinberg equilibrium p-values for $O P R M 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population; bolded and italicized values are significant after Bonferroni correction ( $\mathrm{p}=7.32 \times 10^{-6}$ ). Supplemental Table 17 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 18. Hardy-Weinberg equilibrium p-values for COMT single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five superpopulations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. N is equal to the number of individuals in each population; bolded and italicized values are significant after Bonferroni correction ( $p=4.97$ X $10^{-5}$ ). Supplemental Table 18 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).


Supplemental Figure 3. Distribution of pairwise linkage disequilibrium p-values < 1 for UGT2B7 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five major global super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Each boxplot represents a single populations; the center horizontal line represents the mean, the lower and upper boundaries of each box represent the first and third quartiles, respectively, the vertical dashed lines indicate plus/minus three times the interquartile range, and closed circles indicate outliers; $N$ is equal to the number of individuals in each population; p-values for specific pairwise loci comparisons may be shared upon request.


Supplemental Figure 4. Distribution of pairwise linkage disequilibrium p-values < 1 for $A B C B 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five major global super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Note that tests for pairwise LD were only performed for those loci which deviated from Hardy-Weinberg equilibrium expectations against all other loci. Each boxplot represents a single populations; the center horizontal line represents the mean, the lower and upper boundaries of each box represent the first and third quartiles, respectively, the vertical dashed lines indicate plus/minus three times the interquartile range,
and closed circles indicate outliers; N is equal to the number of individuals in each population; p-values for specific pairwise loci comparisons may be shared upon request.


Supplemental Figure 5. Distribution of pairwise linkage disequilibrium p-values < 1 for OPRM1 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five major global super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Note that tests for pairwise LD were only performed for those loci which deviated from Hardy-Weinberg equilibrium expectations against all other loci. Due to computational limitations, all pairwise loci comparisons could not be represented in the same boxplot; boxplots are separated according to numerical order of the first locus in
the pairwise comparison. Each boxplot represents a single populations; the center horizontal line represents the mean, the lower and upper boundaries of each box represent the first and third quartiles, respectively, the vertical dashed lines indicate plus/minus three times the interquartile range, and closed circles indicate outliers; N is equal to the number of individuals in each population; $p$-values for specific pairwise loci comparisons may be shared upon request.


Supplemental Figure 6. Distribution of pairwise linkage disequilibrium p-values < 1 for COMT single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five major global super-populations and 26 sub-populations based on 1000 Genomes Project Phase 3 genotype data. Each boxplot represents a single populations; the center horizontal line represents the mean, the lower and upper boundaries of each box represent the first and third quartiles, respectively, the vertical dashed lines indicate plus/minus three times the interquartile range, and closed circles indicate outliers; $N$ is equal to the number of individuals in each population; p-values for specific pairwise loci comparisons may be shared upon request.


Supplemental Figure 7. Heat maps of pairwise linkage disequilibrium p-values for UGT2B7 single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations. Super-populations are separated by a diagonal red line.


Supplemental Figure 8. Heat map of linkage disequilibrium p-values for $A B C B 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations. Super-populations are separated by a diagonal red line. Note that pairwise LDs were only performed for those loci which deviated from Hardy-Weinberg equilibrium expectations.


Supplemental Figure 9. Heat map of linkage disequilibrium p-values for $O P R M 1$ single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations. Super-populations are separated by a diagonal red line. Note that pairwise LDs were only performed for those loci which deviated from Hardy-Weinberg equilibrium expectations.


Supplemental Figure 10. Heat map of linkage disequilibrium p-values for COMT single nucleotide polymorphisms, insertion/deletion polymorphisms, and copy number variants in five super-populations. Super-populations are separated by a diagonal red line.

Supplemental Table 19. Variant effect prediction for 613 polymorphisms in the UGT2B7 gene region. Supplemental Table 19 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 20. Variant effect prediction for 5,986 polymorphisms in the ABCB1 gene region. Italicized polymorphisms are found within regions of overlap between $A B C B 1$ and RUNDC3B. Supplemental Table 20 can be viewed at The Pharmacogenomics Journal's
website
for
this
article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 21. Variant effect prediction for 6,831 polymorphisms in the OPRM1 gene region. Supplemental Table 21 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 22. Variant effect prediction for 1,007 polymorphisms in the COMT gene region. Italicized polymorphisms are found within regions of overlap between COMT and TXNRD2 or ARVCF. Bolded polymorphisms were assigned SIFT, PolyPhen-2, and/or PROVEAN scores, however, they align with amino acids in ARVCF, not COMT. Supplemental Table 22 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

Supplemental Table 23. Pairwise linkage disequilibrium p-values for 1,349 polymorphisms across CYP2D6, UGT2B7, $A B C B 1, O P R M 1$, and $C O M T$ that were assigned SIFT, PolyPhen2, PROVEAN, and/or HSF scores leading to damaging, or most likely damaging, predictions. Bolded and italicized p-values are significant after Bonferroni correction ( $\mathrm{p}=5.50 \times 10^{-8}$ ). Supplemental Table 23 can be viewed at The Pharmacogenomics Journal's website for this article (https://www.nature.com/tpj/journal/vaop/ncurrent/full/tpj201713a.html).

## CHAPTER 3

# Full-Gene Haplotypes Refine CYP2D6 Metabolizer Phenotype Inferences 

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Frank R Wendt
Antti Sajantila
Rodrigo S. Moura-Neto
August E Woerner
Bruce Budowle


#### Abstract

CYP2D6 is a critical pharmacogenetic target and polymorphisms in the gene region are commonly used to infer enzyme activity score and predict resulting metabolizer phenotype: poor, intermediate, extensive/normal, or ultrarapid which can be useful in determining cause and/or manner of death in some autopsies. Current genotyping approaches are incapable of identifying novel and/or rare variants so CYP2D6 star allele definitions are limited to polymorphisms known a priori. While useful for most predictions, recent studies using massively parallel sequencing data have identified additional polymorphisms in CYP2D6 that are predicted to alter enzyme function but are not considered in current star allele nomenclature. The 1000 Genomes Project data were used to produce full-gene haplotypes, describe their distribution in super-populations, and predict enzyme activity scores. Full-gene haplotypes generated lower activity scores than current approaches due to inclusion of additional damaging polymorphisms in the star allele. These findings are critical for clinical implementation of metabolizer phenotype prediction because a fraction of the population may be incorrectly considered normal metabolizers but actually may be poor or intermediate metabolizers.


## Introduction

The cytochrome p450 family 2 subfamily D polypeptide 6 (CYP2D6) enzyme is part of a large family of CYPs responsible for a substantial portion of hepatic Phase I metabolism of foreign compounds and endogenous toxins [1,2]. The enzyme has been implicated in drug metabolism variation of clinical and medico-legal relevance [3,4]. Current methods of pharmacogene analyses employ targeted approaches, such as genome wide association studies of candidate single nucleotide polymorphisms (SNPs) and SNP-targeted massively parallel sequencing (MPS) of known a priori SNPs and/or insertion/deletion polymorphisms (INDELs) [5]. The CYP2D6 allele nomenclature, in the Human Cytochrome P450 Allele Nomenclature Database (HCYPAND) [6], identifies and defines polymorphisms that confer each CYP2D6 star (*) allele (the collection of polymorphisms within the gene region). CYP2D6 * allele genotypes (g), or diplotypes, commonly provide inferences of metabolizer phenotype (MP; poor [gPM], intermediate [gIM], normal/extensive [gNM/gEM], or ultrarapid [gUM] CYP2D6 activity) $[1,2,6,7]$. It has been demonstrated both clinically and medico-legally that CYP2D6 information can result in increased prescription efficacy and inference of idiosyncratic effect during accident reconstruction [8-12]. In fact, Koren, et al. [8] and Koski, et al. [9,10] have used targeted genotyping of CYP2D6 to make inferences regarding the cause and/or manner of death in a series of medico-legal cases. However, targeted genotyping approaches inherently are incapable of revealing novel polymorphisms that may further refine CYP2D6 * alleles and the associated metabolic differences observed in clinical cases and medico-legal investigations. MPS of the full gene region has the potential to reveal additional polymorphisms and refine predictions of CYP2D6 activity.

Wendt, et al. [13] characterized 418 polymorphisms in CYP2D6 exons, introns, 3' and 5' untranslated regions, and promoter region in the 1000 Genomes Project dataset. 97 (23.2\%) of the polymorphisms are currently used by HCYPAND to classify some of the < 150 CYP2D6 * alleles observed to date. The remaining 321 polymorphisms have a wide range of allele frequencies in the African (AFR), Admixed American (AMR), East Asian (EAS), European (EUR), and South Asian (SAS) super-populations. Most notable are those polymorphisms predicted to damage, or most likely damage, CYP2D6 function. Ignoring these loci when determining CYP2D6 * alleles may lead to inaccurate predictions of enzyme function and incorrect conclusions for drug therapy or potential cause and/or manner of death investigations. The HCYPAND database has established inclusion criteria for newly observed CYP alleles [14] which put more emphasis on enzyme-altering polymorphisms for the sake of providing minimalist nomenclature. However, in medico-legal autopsy cases where incident reconstruction and cause and/or manner of death may be inferred from toxicology and genetic data [8-10], a more comprehensive and inclusive nomenclature may be necessary. Herein, all typed loci from the 1000 Genomes Project data were used to generate and characterize fullgene CYP2D6 haplotypes. These data indicate that the phenotypic impact of some previously defined CYP2D6 * alleles may have been mischaracterized due to damaging polymorphisms occurring elsewhere in the gene relative to a HCYPAND causal SNP or INDEL. Mischaracterizations based on targeted genotyping and traditional * allele nomenclature may have clinical and medico-legal consequences, as a fraction of 1000 Genomes Project samples may be inaccurately placed into MP categories.

## Materials and Methods

Polymorphisms in the CYP2D6 gene region (introns, exons, 5' and 3' untranslated regions [UTRs], and promoter) were downloaded from Phase 3 of the 1000 Genomes Project [15,16] and analyzed individually in 5 super- and 26 sub-populations (Table S1) according to Wendt, et al. 2017 [13]. 1000 Genomes Project CYP2D6 haplotypes containing reportedly phased polymorphisms [17] were aligned to the hg 38 and hg 19 reference genomes and the M33388 GenBank accession reference sequence (Table S2) for ease of community comparison [18-21]. CYP2D6 full-gene haplotypes were named relative to the reverse DNA strand of three reference sequences with the following nomenclature format: reference sequence (genome name or GenBank Accession Number)- HCYPAND CYP2D6* allele designationpolymorphism rs number, if known, followed by the base at that position. Note that if an rs number is not provided for a specific location, the nucleotide position and base change, relative to the indicated reference, are provided. For example, haplotype 1 is named M33388-CYP2D6: 5157insCCCACCCCTT, hg19-CYP2D6: rs28439297A; rs28680494G; rs1080983G; rs1080985C; rs28735595A; rs28624811C; rs28633410G; rs1808995G; rs1080996C; rs74644586C; rs76312385T; rs75276289G; rs28695233A; rs1081000A; rs28371699G; rs28371701C; rs28371702T; rs1058164G; rs16947C; rs28371730G; rs1135840G; rs116390392G; rs71184866insACA; rs35028622T; rs34386013T, and hg38-CYP2D6: None, relative to the M33388, hg19, and hg38 reference genomes, respectively.

Full-gene CYP2D6 haplotypes and diplotypes for 2,504 individuals in five super- and 26 sub-populations were created using excel-based workbooks. Private mutations (those polymorphisms observed once in the 1000 Genomes dataset), except those considered clinically relevant by HCYPAND and those predicted by Wendt, et al. 2017 [13] to damage,
or most likely damage, the resulting protein, were removed from haplotype formation to simplify downstream analyses. 1000 Genomes Project haplotypes were named according to the same convention described above. Genetic Data Analysis [22] was used to determine haplotype and diplotype frequencies, observed (Ho) and expected (He) heterozygosities, pairwise genetic distances, and perform tests for detection of departures from Hardy-Weinberg Equilibrium (HWE). TreeView Version 1.6.6 Build 7601 [23,24] and RStudio® [25] were used to create phylogenetic trees and multidimensional scaling (MDS) plots, respectively. Network analyses were performed using Population Analysis with Reticulate Trees (PopART) [26]. For comparison to HCYPAND CYP2D6 * alleles, full-gene haplotypes lacking amino acid changes and damaging intronic sequences are considered derivatives of CYP2D6*1 and full-gene haplotypes conferring R296C (or C296R for hg19-based haplotypes) and S486T (or T486S for hg19-based haplotypes) but no other amino acid changes or damaging intronic polymorphisms were considered derivatives of CYP2D6*2.

Activity scores were assigned to each allele (i.e., $0,0.5,1$, or 2 ) and individual (i.e., 0 , $0.5,1,1.5,2$, or 3 ) in two ways: (1) Full-gene haplotypes were assigned a most similar HCYPAND -recognized allele which was then assigned an activity score based on Gaedigk, et al. [27] without considering the impact of additional polymorphisms not recognized by HCYPAND [6]; (2) Considering all polymorphisms, a best- and worst-case activity score were assigned to each full-gene haplotype. For example, haplotype 33 (M33388-CYP2D6: 310T; 843G; 1067G; 5157insCCCACCCCTT) received an activity score of 1 based on absence of HCYPAND causal polymorphisms only (resembling a normally active * allele). The presence of non-HCYPAND intronic polymorphism rs78854695, 1067G, damages splicing [13] but its
specific impact on CYP2D6 has not been confirmed empirically. So haplotype 33 was assigned best- and worst-case activity scores of 0.5 and 0 , respectively.

## Results

Histograms of SIFT [28-33], PolyPhen-v2 [28,34,35], and PROVEAN [36-38] scores from Wendt, et al. [13] for HCYPAND-recognized and non-HCYPAND polymorphisms (Figure 1) indicate that 29, 20, and 30 polymorphisms, respectively, from the 1000 Genomes Project dataset for CYP2D6 are predicted to negatively impact protein function. After removal of 138 private mutations, except those considered causal by HCYPAND and those considered damaging or most likely damaging based on Wendt, et al. [13], 446 unique full-gene haplotype string sequences were observed (Table S2). Full-gene CYP2D6 haplotypes 11, 3, and 1 are identical to reference sequences M33388, hg19, and hg38, respectively. A majority of haplotypes were observed once in the global population so the average global frequency of full-gene CYP2D6 haplotypes was quite low ( $0.00224 \pm 0.0115$ with a range of 0.165 (haplotype 1) to 0.000200 (haplotypes 205 through 446)). Haplotypes 1 through 18, had global frequencies $\geq 1 \%$, with an average frequency of $0.0394 \pm 0.0438$ (Table 1 and Figure 2). The average super-population frequencies for haplotypes 1 through 18 were $0.0348 \pm 0.0382$ in $\mathrm{AFR}, 0.0508 \pm 0.0832$ in AMR, $0.0110 \pm 0.0169$ in EAS, $0.0539 \pm 0.0559$ in EUR, and 0.0638 $\pm 0.102$ in SAS.


Figure 1. Distribution of variant effect prediction for Clinical Pharmacogenetics Implementation Consortium polymorphisms and those not used for CYP2D6 nomenclature. Distribution of Sort Intolerant From Tolerant (SIFT) (A) [28-33], Polymorphism Phenotyping v2 (PolyPhen-v2) (B) [28,34,35], and Protein Variant Effect Analyzer (PROVEAN) (C) [36-38] scores from Wendt, et al. [13] for The Human CYP Allele Nomenclature Database recognized polymorphisms (black bars) and polymorphisms not considered by the database (red bars). Arrows indicate the threshold applied to scores from each algorithm to predict the damaging or benign effect a polymorphism has on protein function; scores $<0.05$, > 0.5, <-2.5 for SIFT, PolyPhen-v2, and PROVEAN, respectively, may impact protein function.


Figure 2. CYP2D6 haplotype frequencies. Observed frequencies of 446 full-gene CYP2D6 haplotypes in five major super-populations (African [AFR], Admixed American [AMR], East Asian [EAS], European [EUR], and South Asian [SAS]). The inset graph shows the frequency of those haplotypes with greater than 30 observations globally.

Table 1. Full-gene CYP2D6 haplotypes with $\geq \mathbf{1 \%}$ global frequency. Eighteen cytochrome p450 family 2, subfamily D, polypeptide 6 (CYP2D6) full-gene haplotypes with global allele frequencies $\geq 1 \%$ in the 1000 Genomes Project dataset. Italicized nucleotide positions and rs numbers indicate polymorphisms that change the amino acid sequence relative to the indicated reference genome; underlined nucleotide positions and rs numbers alter CYP2D6 function [6,27,39-41].

| $\begin{aligned} & \text { Haplotype } \\ & \text { Number } \end{aligned}$ | Most Similar CYP2D6 Allele | Reported Activity | Gaedigk, et al. Activity Score | Full-gene Best Case Activity Score | Full-gene Worst Case Activity Score | м33388 Nomenclature | M33388 Amino Acid Changes | Hg19 Nomenclature | Hg19 Amino Acid Changes | Hg38 Nomenclature | Hg38 Amino Acid Changes |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | Nomal | 1 | 1 | 1 | M33388-CYP206:5157insCCCACCCCTT | - | hg 19-CYP2D6: rs28439297A; rs28680494G; rs1080983G; rs 1080985C; rs28735595A; rs28624811C; ; rs28633410G; rs 1808995G; rs1080996C; rs74644586C; ; rs76312385T; rs75276289G; ;s88695233A ; rs 1081000A: rs28371699G; rs28371701C; rs28371702T: rs1058164G; rs16947C; rs28371730G; rs1135840G; rs116390392G: rs71184866insACA; rs35028622T; rs34386013T | Splice Defect; C296R; T486S | hg38-CYP2D6: None | - |
| 2 | 4 | None | 0 | 0 | 0 | M33388-CYP2D6:-2060G;-2053T;-1426T 1235G; -1000A; 100T; 310T; 843G; 1039T; 1661C; 2097G; 3582G; 4180C; 4401T; 4719G; 4808G; 4864C; 5157nsCCCACCCCTT | P34S; Splice Defect; S486T | hg 19-CYP2D6: rs 1080983G; rs 1080985C rs28633410G; ; Is 1065852T; rs 1808995G; rs 1080996C; rs74644586C; rs76312385T; rs75276289G; rs28695233A; rs1081000A; rs28371701C; ; rs 1081003T; rs58440431G rs16947C; rs2004511G; rs28371730G; rs71184866ins 1 16390392G; | P345; C296R | hg38-CYP2D6:rs28439297G; rs28680494T; rs28588594T; rs28735595G; rs1080989A; $\frac{\text { rs1065852T ; rs28371699T; rs28371702G }}{\text { rs1081003T; rs1058164C; rs } 58440431 \mathrm{G} \text {; }}$ rs2004511G; rs1135840C; rs28371738T; rs35028622G; rs4078247G; rs34386013C | P34S; Splice Defect; S486T |
| 3 | 2 | Normal | 1 | 1 | 1 | Мз3388-CYP206: -2060G: 2053T;-1770A; 1584G; 1235G: 740T: 678 A ; $214 \mathrm{C} ;$;221A 223G; 227C; 232C: 233C; 245G; 310T; 746G 843G: 1661C; 2850T; 3584A; 4180C; 4481A 4655delACA; 4719G; 4864C $5157 \mathrm{~ns} C C C A C C C C T$ | Splice Defect; R296C; S486T | hg19-CYP2D6: None | - | hg38-CYP2D6: rs28439297G; rs28680494T; <br> rs1080983A; rs1080985G; rs28735595G; <br> rs28624811T; rs28633410A; rs 1808995C; rs1080996A; rs74644586G; rs76312385C; <br> rs75276289C; rs28695233C; rs1081000G; <br> rs28371699T; rs28371701G; rs28371702G <br> rs 1058164C; rs 16947T; rs28371730A; <br> rs1135840C; rs116390392A; <br> rs71184866delACA; rs35028622G; rs34386013C | Splice Defect; R296C; S486T |
| 4 | 2 | Nomal | 1 | 1 | 1 | Мзз388-СYP2D6:-2060G;-2053T;-1770A; 1235G; 740T; 678A; 214C; 221A; 223G; 227C 232C: 233C: 245G; 310T: 746G; 843G; 1661C 2850T; 2988A; 3584A; 4180C; 4481A; 4655delaci; 4719G; 4864C 5157insCCCACCCCTT | Splice Defect R296C; Splice Defect; S486T | ng 19-CYP206: rs 1080985C; [s28371725A | Splice Defect | hg38-CYP2D6: rs28439297G; rs28680494T rs1080983A; rs28735595G; ; r28624811T; <br>  rs28695233C; rs1081000G; rs28371699T; rs28371701G; rs28371702G; rs1058164C; rs 16947T; ; r28371725A; rs28371730A; rs1135840C; rs 1 16390392A rs71184866delACA; rs35028622G; rs34386013C | Splice Defect; R296C; Splice |
| 5 | 17 | Decreased | 0.5 | 0.5 | 0.5 | M3338-CYP206:-2060G:-2055T:-1235G; 245G; 310T; 843G: 1023A; 1661C; 2850T: 3584A; 4180C; ;4799A; 47 19G; $47666 ; 48644 \mathrm{C}$ 5157insCCCACCCCT | Splice Defect; T1071; R296C S486T | hg19-CYP2D6: rs 1080983G; rs1080985C; rs28633410G; rs28371701C; rs28371706T rs1 16390392G; rs71184866insACA; rs 4078249A; rs4078248A |  | hg38-CYP2D6: rs28439297G; rs28680494T; rs28735595G; rs28624811T; rs1808995C; rs1080996A; rs74644586G; rs76312385C; rs75276289C; rs28695233C; rs1081000G; rs75276289C; ; s28695233C; rs 1081000G; rs28371699T; ; s28371702G; rs28371706T rs1058164C; rs 16947T; rs28371730A; rs 4078248A: rs34386013C rs 1135840C; rs4078249A; rs35028622G | Splice Defect; T1071; R296C S486T |
| 6 | 1 | Nomal | 1 | 1 | 1 | M33388-CYP2D6:-43insG; 4928A; 5157insCCCACCCCTT |  |  rs28833410G; ; rs 75885559 insG; ; s 1808995G <br>  rs28371699G; rs28371701C; ;s28371702T; rs1058164G; s16947C; ; r28371730G; rst 1 135840G; ; Is 1 16390392G; <br>  | Splice Defect; C296R; T486S | hg38-CYP2D6: rs750855599 ${ }^{\text {nsG }}$; rs 1 12886416 A |  |
| 7 | 4 | None | 0 | 0 | 0 |  984G; 997G; 1661C: 1846A: 2097G; 3582G; 4180C; 4401T; 4719G; 4808G; 4864C 5157 nnCCCACCCCT | P34S; L91M; H94R; Splice Defect Splice Defect S486T | hg19-CYP2D6: rs1080983G; rs1080985C; rs28588594T; rs 1080989A; rs28624811C; <br>  rs75276289G; rs28695233A; rs1081000A; rs rs283771703A; rs28371704G; ; rs28371705G; rs3892097A; rs58440431G; rs 16947C; rs2004511G; rs28371730G; rs28371738T; rs1 16390392G; r r71184866insACA; rs 4078247 G | P34S;L91M; H94R; <br> Splice Defect: <br> C296R | hg38-CYP2D6: rs28439297G; rs28680494T rs28588594T; rs28735595G; rs1080989A rs28371702G; rs28371703A; rs28371704G rs28371705G; r 1 1058164C; rs3892097A; rs28371738T; ; s355028622G; rs4078247G; rs34386013C | P34S; L91M; H94R; <br> Splice Defect: <br> Splice Defect <br> S486T |
| 8 | 29 | Decreased | 0.5 | 0.5 | 0 | м33388-CYP206:-2060G;:2053T:-1594C, <br>  <br>  | Splice Defect; V136I; R296C V338M; S486T V38M; S486T | hg19-CYP2D6: rs1080983G; rs1080984C; rs1080985C; rs 1080986A; rs 1080987A; rs1080996C; rs74644586C; ; ss76312385T; rs75276289G; rs28695233A; rs1081000A rs267608275delC; rs661736512A; rs76327133T; rs80262685G; r $\mathrm{r} 75203276 \mathrm{~A} ;$ rs59421388A: rs28371730G; rs 116390392G rs71184866insACA | Splice Defect; V136I; V338M | hg38-CYP2D6: rs28439297G; rs28680494T; rs 1080984C; rs 1080986A; rss 1080987A; rs28371699T; rs267608275delC; rs28371701G; $\stackrel{\text { rs28371702G; ; rs61736512A; rs1 1058164C; }}{\text { rs76327133T } \text {; }}$ rs 16947 T ; rs59421388A: rs 1135840C; rs35028622G; rs34386013C | Splice Defect; V136I; R296C; V338M; S486T |
| 9 | 17 | Decreased | 0.5 | 0.5 | 0.5 | M3338-CYPPDE:-2060G:-2053T:-1235G; 245G: 310T: 654T: 843G: 1023A; 1661C; 2850T: 3584A; 4180C; $4709 \mathrm{~A} ; ~ 4719 \mathrm{G} ;$; 4766A; 4864C; 5157 nsCCCACCCCT | Splice Defect <br> T1071; R296C <br> S486T | hg 19-CYP2D6: rs 1080983G; rs 1080985C; rs28633410G; rs376217512T; rs28371701C; rs28371706T; rs116390392G <br> rs71184866insACA; rs4078249A; rs4078248A | T1071 | hg38-CYP2D6: rs28439297G; rs28680494T rs28735595G; rs28624811T; rs1808995C; rss $75276289 \mathrm{C} ;$; rs28695233C; rs1081000G; rs rs28371699T; rs376217512T; rs28371702G; rs28371706T; rs1058164C; rs 16947T; rs35028622G; rs4078248A; rs34386013C | Splice Defect; T1071; R296C S486T |

Table 1 (continued). Full-gene CYP2D6 haplotypes with $\geq \mathbf{1 \%}$ global frequency. Eighteen cytochrome p450 family 2, subfamily D, polypeptide 6 (CYP2D6) full-gene haplotypes with global allele frequencies $\geq 1 \%$ in the 1000 Genomes Project dataset. Italicized nucleotide positions and rs numbers indicate polymorphisms that change the amino acid sequence relative to the indicated reference genome; underlined nucleotide positions and rs numbers alter CYP2D6 function [6,27,39-41].

| Happotype Number | Most Simlar crppote Alle | Reported Activity | $\begin{gathered} \text { Gaedigk, ot } \\ \text { al Altativy } \\ \text { Score } \end{gathered}$ | $\begin{gathered} \text { Full-gene } \\ \text { Best Case } \\ \text { Activity Score } \end{gathered}$ | $\begin{array}{\|c\|} \text { Full-gene } \\ \text { Worst Case } \\ \text { Activity Score } \end{array}$ | M33388 Nomenclature | M33388 Amino Acid Changes | Hg19 Nomenclature | Hg19 Amino Acid Changes | Hg38 Nomenclature | Hg38 Amino Acid Changes |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 10 | 4 | None | 0 | 0 | 0 | M33388-CYP2D6:-2060G;-2053T;-1426T: 1235G;-1000A; 100T; 310T; 746G; 843G; 974A 4180C; 4401T; 47 19G; 4808G; 4864 C | P34S; L91M; H94R; <br> Splice Defect; <br> Splice Defect; <br> S486T | hg19-CYP2D6: rs 1080983G; rs 1080985C; rs28633410G; rs1065852T; rs 1808995G; rs 1080996C; rs74644586C; rs76312385T rs 75276289G; rs28695233A; rs 1081000A; Is I 3892097 A ; rs58440431G; rs 16947C; rs200451 1G; rs28371730G; rs28371738T rs 116390392G: rs71184866ins ACA; rs4078247G; | P34S; L91M; H94R; Splice Defect; C296R | hg38-CYP2D6: rs28439297G; rs28680494T; rs28588594T; rs28735595G; rs 1080989A rs1065852T; rs28371699T; rs28371701G; ; rs28371702G; rs28371703A; rs28371704G; rs28371705G;rs1058164C; rs3892097A rs58440431G; rs2004511G; rs 1135840C; rs28371738T; rs35028622G; rs4078247G rs 34386013 C ; rs536156813deICCCACCCCTT | P34S; Splice Defect;L91M; Defect; S486 T |
| 11 | 1 | Normal | 1 | 1 | 1 | M33388-CYP206: None |  |  | Splice Defect; <br> C296R; T486S | h938-CYP2066: rs5361 1568 13delCCCACCCCTT |  |
| 12 | 1 | Normal | 1 | 1 | 1 | Мз3з88-СҮP2D6: 1170А 5157 insCCCACCCCTT | - | hg19-CYP2D6: rs28439297A; rs28680494G rs 1080983G; rs 1080985C; rs28735595A; rs286248 rs 108096C; rs $746844586 \mathrm{C} ;$ rs $76312385 \mathrm{~T} ;$ rs 75276289 G ; rs28695233A; rs1081000A; rs28371699G; rs28371701C; rs28371702T rs 1081004 A ; rs 1058164 G ; rs 16947 C rs28371730G; rs 1135840 G ; rs 16390392G rs71184866insACA; rs35028622T; rs34386013T | Splice Defect; <br> C296R; T486S | hg38-CYP206: : Is 1081004A | . |
| 13 | 1 | Normal | 1 | 1 | 1 | м33388-CYP206: 310T; 8433: 1067 \% | Splice Defect; Splice Defect |  rs28624811C; rs28633410G; rs 1808995G rs 1080996C; ris 74644586C; ; r776312385T <br>  rs 16947C ; rs28371730G; rs ITI 35840 G <br>  <br>  | Splice Defect; C296R; T486S | hg38-CYP2D6: rs28371699T; rs28371702G; rs78854695G; rs536156813delCCCACCCCTT | Splice Defect; Splice Defect |
| 14 | ${ }^{35}$ | Normal | 1 | 1 | 1 | M33388-CYP2D6:-2060G:-2053T:-1770A; 1584G: -1235G: $740 \mathrm{~T}: 678 \mathrm{~A} ; 31 \mathrm{~A}:=214 \mathrm{C}: 221 \mathrm{~A}$ 223G:227C; 232C; 233C; 245G;310T; 746 G 4655delACA; 4719G; 4864C $5157 \mathrm{ins} C C C A C C C C T T$ | V11M; Splice Defect; S486T | h919-CYP206: : 5769258 A | V11M | hg38-CYP2D6: : rs28439297G; rs28680494T rs 1080983A; rs1 1080985G; rs28735595G; <br>  <br>  <br>  rs28371702G; rs 1058164C; rs 16947T: rs28371730A: rss 135840C; rs 116390392 A rs71 184866delACA; rs35028622G; rs34386013C | V11M; Splice S486T |
| 15 | 1 | Normal | 1 | 1 | 1 | мз3388-CYP2D6: 498А; 5154T; 5157insCCCACCCCTT |  | hg19-CYP2D6: rs28439297A; rs28680494G <br>  rs 1808995G; r s1080996C; rs74644586C; <br>  rs28371702T: rs1 058164G; rs16947C: Ts28371730G; rst 135840G; rs 116390392G; rssin rs37415353932T | Splice Defect; <br> C296R; T486S |  |  |
| 16 | 1 | Nomal | 1 | 1 | 1 | M33388-CYP206: 270A; 5157nnsAGGGGTGGG - |  | hg19-CYP2D6 : rs28439297T: rs28680494C: is 1080983 ; ; rs 10809859 ; rs28735595T; rs 1080996G; rs74644586G; ;s76312385A; rs75276289C; ; r28695233T; ; rs 1081000T; rs29001678A; rs28371699C; rs28371701G; <br>  rs71184866insTGT; r s35028622A; rs34386013A | Splice Defect; <br> C296R; T486S | n938-CYP202: : s29001678A |  |
| 17 | 1 | Normal | 1 | 1 | 1 | M33388-CYP206: 270A; 5157nnsAAGGGTGGG - |  | hg19-CYP2D6: rs28439297T; rs28680494C rs 1080983C; rs 1080985G; rs28735595T. rs 1080996G; rs74644586G; rs76312385A; rs 75276289 C ; rs28695233T; rs 1081000T; rs29001678A; rs28371699C; rs28371701G; $\frac{\text { rs28371702A; rs }}{\text { rs } 28371730 \mathrm{C} \text {; } 1135840 \mathrm{C} \text {; rs } 116390392 \mathrm{C} \text {; } ; ~}$ rs 71 184866insTGT; rs35028622A; rs34386013A | Splice Defect; <br> C296R; T486S | h938-CYP2026: s 290016778 A |  |
| 18 | 1 | Normal | 1 | 1 | 1 | Мз3388-СҮP2D6:5154A 5157insAAGGGGTGGG |  | hg19-CYP2D6: : rs28439297T; rs28680494C rs 1080983C; rs 1080985G; rs28735595T; <br>  rs75276289C; ; rs28695233T; rs 1081000T; rs28371699C; rs28371701G; ; s28371702A rs 1135840C; ; rs 16390392C: rs7 1184866insTGT rs35028622A; rs343860 3 A; rs374153932A | Splice Defect; <br> C296R; T486S | ng38-CYP2D6: 1 r374153932A | - |

One haplotype observed in this study was consistent with HCYPAND CYP2D6* allele reference list (CYP2D6*1A,5 M33388-CYP2D6: None, hg19-CYP2D6: rs28439297A; rs28680494G; rs1080983G; rs1080985C; rs28735595A; rs28624811C; rs28633410G; rs10808995G; rs1080996C; rs74644586C; rs76312385T; rs75276289G; rs28695233A; rs1081000A; rs28371699G; rs28371701C; rs28371702T; rs1058164G; rs16947C; rs28371730G; rs1135840G; rs116390392G; rs71184866insACA; rs35028622T; rs34386013T; rs536156813delCCCACCCCTT, hg38-CYP2D6: rs536156813delCCCACCCCTT). Though not specifically reported in the HCYPAND CYP2D6 * allele table, 407 ( $91.3 \%$ ) haplotypes could be associated with at least one * allele based on the presence of defining amino acid changes and causal polymorphisms, however, 38 (i.e., $8.52 \%$ ) of them could not be associated. These 38 haplotypes were observed $125 / 5008$ times ( $2.50 \%$ ) in the 1000 Genomes Project and contain combinations of functionally relevant polymorphisms [6]. Figure 3 and Figure S1 represent the variant composition of haplotypes 1 through 18 and all 446 haplotypes, respectively. The average number of polymorphisms per haplotype was $15 \pm 10,20 \pm 10$, and $14 \pm 10$ as designated by comparison with the M33388, hg 19 , and hg38 reference sequences, respectively. The majority of each haplotype is functionally irrelevant polymorphic sites; however, 326, 328, and 326 haplotypes harbor a damaging, or most likely damaging, variant relative to the M 33388 , hg 19 , and hg 38 reference genomes, respectively.


Figure 3. CYP2D6 haplotype composition. Haplotype composition of 18 full-gene CYP2D6 star alleles, with global frequencies $\geq 1 \%$, aligned to GenBank accession M33388 (A), hg 19 (B), and hg38 (C). Variant effect predictions performed by Wendt, et al. [13] using Sort Intolerant From Tolerant (SIFT) [28-33], Polymorphism Phenotyping v2 (PolyPhenv2)[28,34,35] Protein Variant Effect Analyzer (PROVEAN) [36-38], and Human Splicing Finder [42].

Network analysis was performed to determine the relatedness of two sets of haplotypes: (1) haplotypes having $\geq 1 \%$ global haplotype frequency (haplotypes 1-18; Figure 4), and (2) haplotypes observed more than once in the entire 1000 Genomes Project dataset (haplotypes 1-204; Figure S2). In Figure 4 and Figure S2, the haplotypes with relatively low global frequencies appear to be derived from the major haplotypes (1, 2, and 3). All major haplotypes except 15 and 17 were observed in the AFR super-population, though the frequency is relatively low due to the AFR population having the widest haplotype spread (Figure S2). Haplotype 9 is exclusive, and haplotypes 5, 6, 9, 13, and 18 are almost exclusive, to the AFR super-population. The clustering of rare haplotypes suggests that these may be specific to one
super-population, such as AFR (minor haplotypes stemming from haplotypes 5, 6, 8, and 9) or EAS (minor haplotypes stemming from haplotypes 2, 15, and 17).


Figure 4. Network analysis of CYP2D6 haplotypes. Network analysis of CYP2D6 full-gene haplotypes 1 through 18. The size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.

There were 961 unique diplotypes observed across 2,504 individuals. The average global diplotype frequency was $0.00104 \pm 0.00336$. Ten diplotypes had global frequencies $\geq$ $1 \%$, with an average global frequency of $0.0275 \pm 0.0177$ (Table 1). The average diplotype frequency in the AFR, AMR, EAS, EUR, and SAS super-populations was $0.00253 \pm 0.00277$, $0.00587 \pm 0.0133,0.00658 \pm 0.0227,0.00466 \pm 0.00688$, and $0.00568 \pm 0.0142$, respectively (Figure 5). The average global Ho and He of CYP2D6 were $0.820 \pm 0.0898$ and $0.861 \pm 0.0923$, respectively. Before Bonferroni correction ( p 0.05), CYP2D6 deviated from HWE
expectations in three super-populations (AFR, AMR, and EUR) and nine sub-populations (ASW, GWD, LWK, MSL, YRI, CLM, CDX, CHS, and GBR) (Figure 6). After Bonferroni correction ( $\mathrm{p}<0.00161$ ), CYP2D6 deviated from HWE expectations in the AFR superpopulation and the ASW and LWK sub-populations.


Figure 5. CYP2D6 diplotype frequencies. Relative CYP2D6 diplotype frequencies in the global population (A), African (B), Admixed American (C), East Asian (D), European (E), and South Asian (F) super-populations. The x- and y-axes indicate the first and second haplotype, respectively, of an individual diplotype; the size of each solid circle is proportional to the frequency of that diplotype.


Figure 6. Heterozygosity and Hardy-Weinberg Equilibrium summary. Observed and expected heterozygosity of CYP2D6 in five major super- and twenty-six sub-populations. Super-populations and their associated sub-populations are color coded (red for African [AFR], blue for Admixed American [AMR], green for East Asian [EAS], yellow for European [EUR], and grey for South Asian [SAS]); the size of each data point corresponds to the HardyWeinberg Equilibrium (HWE) p-value for the locus within that population. The AFR superpopulation and the Luhya in Webuye, Kenya (LWK) and American of African Ancestry in Southwest United States (ASW) sub-populations deviated significantly from HWE expectations after Bonferroni correction ( $\mathrm{p}<0.00161$ ).

Activity scores were assigned to each individual using the functional consequence of the most closely related HCYPAND-recognized * allele to each full-gene haplotype. 282 individuals harbor full-gene haplotypes that, by HCYPAND nomenclature, should confer normal activity enzymes (activity score $=1$ ) but full-gene data reveal additional causal polymorphisms that were predicted to damage enzyme function (Figure 7). Twenty-two of these individuals (21 AFR and 1 AMR) have diplotypes where two full-gene haplotypes produce conflicting activity scores relative to the HCYPAND approach. The average individual activity scores were $1.40 \pm 0.644,1.36 \pm 0.638$, and $1.30 \pm 0.675$ based on HCYPAND guidelines, full-gene best- (Student's t-test; $\mathrm{p}<0.05$ relative to the HCYPAND
approach), and full-gene worst-case (Student's t-test; $\mathrm{p}<0.001$ relative to the HCYPAND approach) haplotype activity score designation. Haplotype 8 (M33388-CYP2D6: 2060G; 2053T; -1594C; -1418A; -1408A; -1235G; -740T; -176A; 310T; 744delC; 746G; 843G; 1659A; 1661C; 2123T; 2215G; 2292A; 2850T; 3183A; 4180C; 4719G; 4864C; 5157insCCCACCCCTT) is responsible for the majority of conflicting MP predictions (111 AFR and 2 AMR individuals). By HCYPAND nomenclature, this haplotype would be assigned an activity score of 0.5 based on similarity to CYP2D6*29 [43]; however, full-gene haplotype data reveal the presence of non-HCYPAND INDEL rs267608275delC (744delC). Due to lack of empirical observation of the influence rs267608275delC has on CYP2D6 function, worstand best-case activity scores of 0 and 0.5 , respectively, were assigned for full-gene haplotypes, indicating that rs267608275delC may or may not further decrease CYP2D6 function. This significant decrease in average activity score suggests that by current CYP2D6 * allele and activity score designation, $\sim 11 \%$ of the individuals in this dataset may be wrongly considered gNM-F, gNM-S, or gIM when they likely belong in the gNM-S, gIM, and gPM categories, respectively.


Figure 7. Activity score predictions using Clinical Pharmacogenetics Implementation Consortium star allele nomenclature and full-gene CYP2D6 haplotypes. Genotypeinferred (g) CYP2D6 MP (gPM: poor; gIM: intermediate; gNM-S: normal/extensive-slow; gNM-F: normal/extensive-fast; gUM: ultrarapid) distribution and average activity scores using The Human CYP Allele Nomenclature Database (HCYPAND) [6] recognized CYP2D6 * alleles and full-gene haplotypes for 2,504 1000 Genomes Project self-reported healthy individuals. Asterisks indicate significant difference in average activity score (Student's t-test; * $\mathrm{p}<0.05$; *** $\mathrm{p}<0.001$ ) compared with HCYPAND nomenclature; vertical black bars indicate the average activity score $\pm$ one standard deviation; individuals with combinations of causal HCYPAND polymorphisms were not assigned to a MP using HCYPAND nomenclature and were assigned to the "unknown" MP category.

MDS plots and unrooted phylogenetic trees (Figure 8) of super-populations show distant separation of the AFR and EAS populations while EUR, AMR, and SAS cluster relatively close together. Considering sub-populations, those belonging to the AFR and EAS super-populations cluster together according to super-population affiliation. Sub-populations belonging to the AMR, EUR, and SAS super-populations have considerable overlap with one another.


Figure 8. Population comparisons using full-gene CYP2D6 haplotypes. Neighbor-joining trees (A and B) and multidimensional scaling plots (C and D) for five super- (A and C) and twenty-six sub-populations (B and D) in the 1000 Genomes Project using pairwise genetic distances based on full-gene CYP2D6 haplotype assignment.

## Discussion

Full-gene CYP2D6 haplotypes may be able to refine MP predictions, ultimately identifying more gIM and gPM individuals than the HCYPAND haplotype nomenclature. The analyses presented here may be limited by the relative low depth of sequence coverage per sample within the 1000 Genomes project database, small sample size for each sub population,
and the precision of variant effect prediction algorithms. These factors impact detection of rare variants that may contribute to CYP2D6 function. In fact, the splice defects defining three * alleles $\left(C Y P 2 D 6^{*} 4, C Y P 2 D 6^{*} 11\right.$, and $\left.C Y P 2 D 6^{*} 41\right)$ were not identified by the software analyses performed in Wendt, et al. and the 843G SNP was incorrectly identified as damaging [6], emphasizing the importance of using variant effect predictors with caution and employing multiple prediction algorithms to identify single nucleotide variants of interest [44]. Additional rare variants will continue to be discovered for PM, IM, and/or UM individuals and/or isolated populations such as Finns or Ashkenazi Jews. While potentially contributing significantly to phenotype, variant effect prediction is not possible; however, the analysis herein may allow for some prediction of phenotype using a number of previously unexploited polymorphisms [45-48]. Additional research is needed (e.g. functional enzyme studies, targeted mutagenesis, and/or quantitative trait analyses) to empirically characterize the phenotype generated from rare polymorphisms, combinations of rare/deleterious polymorphisms in the same haplotype, combinations of deleterious polymorphisms in different genes that may influence one another, and their distributions in under-represented populations.

Copy number variation (CNV) of some CYP2D6 * alleles and CYP2D7 pseudogene conversion do occur in some individuals, namely UMs, and may influence the HWE and LD results [49]. It is likely that some 1000 Genomes Project individuals from the AFR superpopulation carry CNVs based on deviations from HWE expectations [49] but the project does not explore CNV in detail due to limitations of short read sequencing [50,51]. The data presented herein have been analyzed as though only two copies of CYP2D6 are present in each individual so unless an individual contains the SNP rs1135823G>T (1617G>T), the UM phenotype was not identified. A number of unique haplotypes have been identified that may
be true haplotype observations but may also be attributed to duplication of two common haplotypes and/or CYP2D7 pseudogene conversions [52,53]. This phenomenon is particularly true for African populations which exhibit relatively frequent gene duplications (up to 30\%) [54,55]. The development of continuous read single-molecule DNA sequencing strategies, such as nanopore technology [56], may help reduce ambiguity in sequencing regions with a high degree of structural variation.

Unique haplotypes have been identified from the full-gene region of CYP2D6, including introns, exons, $5^{\prime}$ and $3^{\prime}$ UTRs, and the promoter region. While comprehensively assessing the gene itself, there are a number of distant regulatory elements that may impact enzyme function. Wang, et al. [5] identified long-range haplotypes that include polymorphisms within enhancer regions that may refine these haplotype definitions. However, inclusion of such regulatory elements in CYP2D6-based MP predictions may need to be explored further due to potential regulation of other enzymes, potentially confounding MP prediction. Additionally, private mutations not predicted to damage the resulting protein have been removed (note that those considered for HCYPAND-recognized * alleles have been included) from this analysis; however, if incorporated, may produce finer granularity of haplotype definition but likely would not alter activity score unless empirically shown to alter enzyme function.

Full-gene CYP2D6 data have provided additional resolution to the MP compared to predictions used to date, possibly resolving some medico-legal autopsy negative cases. Although empirical data are required to confirm their enzyme activity, approximately $11 \%$ of the healthy individuals in this study may be wrongly identified as NMs according to traditional CYP2D6 genotyping and activity score predictions of MP. Clinically, these individuals likely
would be classified as IM or PM and be treated accordingly. Enhanced predictive capabilities of MP may be made with comprehensive CYP2D6 diplotype information and/or incorporation of a longer-read sequencing platform into the CYP2D6 interrogation workflow.

The case described by Koren, et al. [8] of an application of CYP2D6 genotyping to assist in a medico-legal investigation is a classic example of ultra-rapid metabolism of codeine to morphine. In such cases the medicaments were delivered as a pro-drug (inactive) that must be metabolized in order to deliver the intended effect (e.g., codeine or tamoxifen) [1,2]. Given the prevalence of UM in various populations and the current use of these drugs, it is anticipated that similar cases will occur and molecular autopsies may shed light on the cause and/or manner of death. At the opposite end of the metabolizer phenotype spectrum are PMs and IMs. If considering codeine to morphine metabolism, CYP2D6 genotyping post-mortem may not be informative. However, many antidepressants (e.g., nortriptyline) are active upon administration and depend on CYP2D6 to deactivate the drug. PMs and IMs, based on their CYP2D6 variants, may experience adverse reactions to antidepressants which include, but are not limited to, delayed propagation of myocardium depolarization leading to cardiac arrhythmia, myocardial infarction, and death [11]. In the context of the data presented in this study, $\sim 11 \%$ of individuals may be incorrectly classified as NMs or IMs as their full-gene haplotype data indicate one category lower (i.e., NM by targeted approach is an IM by fullgene approach; IM by targeted approach is a PM by full-gene approach). As such, understanding CYP2D6 haplotype information of all metabolizer phenotypes can be quite relevant to the medico-legal community.

## References

1. Ingelman-Sundberg M, Sim SC, Gomez A, Rodriguez-Antona C. Influence of cytochrome P450 polymorphisms on drug therapies: pharmacogenetic, pharmacoepigenetic and clinical aspects.Pharmacol Ther. 2007 Dec;116(3):496-526. Epub 2007 Oct 9. Review. PubMed PMID: 18001838.
2. Ingelman-Sundberg M. Genetic polymorphisms of cytochrome P450 2D6 (CYP2D6): clinical consequences, evolutionary aspects and functional diversity. Pharmacogenomics J. 2005;5(1):6-13. Review. PubMed PMID: 15492763.
3. Smith HS. Opioid metabolism. Mayo Clin Proc. 2009 Jul;84(7):613-24. doi: 10.1016/S0025-6196(11)60750-7. Review. PubMed PMID: 19567715; PubMed Central PMCID: PMC2704133.
4. Koren G, Cairns J, Chitayat D, Gaedigk A, Leeder SJ. Pharmacogenetics of morphine poisoning in a breastfed neonate of a codeine-prescribed mother. Lancet. 2006 Aug 19;368(9536):704. PubMed PMID: 16920476.
5. Koch WH. Technology platforms for pharmacogenomic diagnostic assays. Nat Rev Drug Discov. 2004 Sep;3(9):749-61. Review. PubMed PMID: 15340385.
6. http://www.cypalleles.ki.se/cyp2d6.htm. Accessed 01JUN2016.
7. Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2017 Jan;19(1):69-76. doi: 10.1038/gim.2016.80. Epub 2016 Jul 7. PubMed PMID: 27388693; PubMed Central PMCID: PMC5292679.
8. Koren G, Cairns J, Chitayat D, Gaedigk A, Leeder SJ. Pharmacogenetics of morphine poisoning in a breastfed neonate of a codeine-prescribed mother. Lancet. 2006 Aug 19;368(9536):704. PubMed PMID: 16920476.
9. Koski A, Ojanperä I, Sistonen J, Vuori E, Sajantila A. A fatal doxepin poisoning associated with a defective CYP2D6 genotype. Am J Forensic Med Pathol. 2007 Sep;28(3):259-61. PubMed PMID: 17721180.
10. Koski A, Sistonen J, Ojanperä I, Gergov M, Vuori E, Sajantila A. CYP2D6 and CYP2C19 genotypes and amitriptyline metabolite ratios in a series of medicolegal autopsies. Forensic Sci Int. 2006 May 10;158(2-3):177-83. Epub 2005 Jul 15. PubMed PMID: 16024198.
11. Kerr GW, McGuffie AC, Wilkie S. Tricyclic antidepressant overdose: a review. Emerg Med J. 2001 Jul;18(4):236-41. Review. PubMed PMID: 11435353; PubMed Central PMCID: PMC1725608.
12. Karlsson L, Zackrisson AL, Josefsson M, Carlsson B, Green H, Kugelberg FC. Influence of CYP2D6 and CYP2C19 genotypes on venlafaxine metabolic ratios and stereoselective metabolism in forensic autopsy cases. Pharmacogenomics J. 2015 Apr; 15(2):165-71. doi: 10.1038/tpj.2014.50. Epub 2014 Sep 23. PubMed PMID: 25245581.
13. Wendt FR, Pathak G, Sajantila A, Chakraborty R, Budowle B. Global genetic variation of select opiate metabolism genes in self-reported healthy individuals. Pharmacogenomics J. 2017 Apr 11. doi: 10.1038/tpj.2017.13. [Epub ahead of print] PubMed PMID: 28398354.
14. http://www.cypalleles.ki.se/criteria.htm. Accessed 14JUN2017.
15. Karolchik D, Hinrichs AS, Kent WJ. The UCSC Genome Browser. Curr Protoc Bioinformatics. 2012 Dec;Chapter 1:Unit1.4. doi: 10.1002/0471250953.bi0104s40. PubMed PMID: 23255150.
16. 1000 Genomes Project Consortium., Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, Korbel JO, Marchini JL, McCarthy S, McVean GA, Abecasis GR. A global reference for human genetic variation. Nature. 2015 Oct 1;526(7571):68-74. doi: 10.1038/nature15393. PubMed PMID: 26432245; PubMed Central PMCID: PMC4750478.
17. IGSR and the 1000 Genomes Project Frequently Asked Questions Web Page. http://www.internationalgenome.org/faq/are-1000-genomes-variant-calls-phased/. Accessed 14JUN2017.
18. Zhou SF, Di YM, Chan E, Du YM, Chow VD, Xue CC, Lai X, Wang JC, Li CG, Tian M, Duan W. Clinical pharmacogenetics and potential application in personalized medicine. Curr Drug Metab. 2008 Oct;9(8):738-84. Review. PubMed PMID: 18855611.
19. https://www.ncbi.nlm.nih.gov/nuccore/M33388?report=GenBank
20. https://www.ncbi.nlm.nih.gov/nucleotide/45024927
21. Gaedigk A, Bhathena A, Ndjountché L, Pearce RE, Abdel-Rahman SM, Alander SW, Bradford LD, Rogan PK, Leeder JS. Identification and characterization of novel sequence variations in the cytochrome P4502D6 (CYP2D6) gene in African Americans. Pharmacogenomics J. 2005;5(3):173-82. Erratum in: Pharmacogenomics J. 2005;5(4):276. Rogan, PK [added]. PubMed PMID: 15768052; PubMed Central PMCID: PMC1440720.
22. Genetic Data Analysis Software. Lewis and Zaykin. 1999.
23. Page, R. D. M. 1996. TREEVIEW: An application to display phylogenetic trees on personal computers. Computer Applications in the Biosciences 12: 357-358.
$\begin{array}{ccc}\text { 24. TreeView } & \text { Version } & \text { 1.6.6 } \\ \text { http://taxonomy.zoology.gla.ac.uk/rod/treeview/treeview_manual.html\#citing_treeview }\end{array}$
24. RStudio Team (2015). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.
25. Population Analysis with Reticulate Trees (PopART). Developed by Jessica Leigh, David Bryant, and Mike Steel. http://popart.otago.ac.nz
26. Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS. The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther. 2008 Feb;83(2):234-42. PubMed PMID: 17971818.
27. McLaren W, Gil L, Hunt SE, Riat HS, Ritchie GR, Thormann A, Flicek P, Cunningham F. The Ensembl Variant Effect Predictor. Genome Biol. 2016 Jun 6;17(1):122. doi: 10.1186/s13059-016-0974-4. PubMed PMID: 27268795; PubMed Central PMCID: PMC4893825.
28. Kumar P, Henikoff S, Ng PC. Predicting the effects of coding non-synonymous variants on protein function using the SIFT algorithm. Nat Protoc. 2009;4(7):1073-81. doi: 10.1038/nprot.2009.86. Epub 2009 Jun 25. PubMed PMID: 19561590.
29. Ng PC, Henikoff S. Predicting the effects of amino acid substitutions on protein function. Annu Rev Genomics Hum Genet. 2006;7:61-80. Review. PubMed PMID: 16824020.
30. Ng PC, Henikoff S. SIFT: Predicting amino acid changes that affect protein function. Nucleic Acids Res. 2003 Jul 1;31(13):3812-4. PubMed PMID: 12824425; PubMed Central PMCID: PMC168916.
31. Ng PC, Henikoff S. Accounting for human polymorphisms predicted to affect protein function. Genome Res. 2002 Mar;12(3):436-46. PubMed PMID: 11875032; PubMed Central PMCID: PMC155281.
32. Ng PC, Henikoff S. Predicting deleterious amino acid substitutions. Genome Res. 2001 May;11(5):863-74. PubMed PMID: 11337480; PubMed Central PMCID: PMC311071.
33. Adzhubei IA, Schmidt S, Peshkin L, Ramensky VE, Gerasimova A, Bork P, Kondrashov AS, Sunyaev SR. A method and server for predicting damaging missense mutations. Nat Methods. 2010 Apr;7(4):248-9. doi: 10.1038/nmeth0410-248. PubMed PMID: 20354512; PubMed Central PMCID: PMC2855889.
34. Adzhubei I, Jordan DM, Sunyaev SR. Predicting functional effect of human missense mutations using PolyPhen-2. Curr Protoc Hum Genet. 2013 Jan; Chapter 7:Unit7.20. doi: 10.1002/0471142905.hg0720s76. PubMed PMID: 23315928; PubMed Central PMCID: PMC4480630.
35. Choi Y, Sims GE, Murphy S, Miller JR, Chan AP. Predicting the functional effect of amino acid substitutions and indels. PLoS One. 2012;7(10):e46688. doi:
10.1371/journal.pone.0046688. Epub 2012 Oct 8. PubMed PMID: 23056405; PubMed Central PMCID: PMC3466303.
36. Choi Y, Chan AP. PROVEAN web server: a tool to predict the functional effect of amino acid substitutions and indels. Bioinformatics. 2015 Aug 15;31(16):2745-7. doi: 10.1093/bioinformatics/btv195. Epub 2015 Apr 6. PubMed PMID: 25851949; PubMed Central PMCID: PMC4528627.
37. Choi Y (2012) A Fast Computation of Pairwise Sequence Alignment Scores Between a Protein and a Set of Single-Locus Variants of Another Protein. In Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine (BCB '12). ACM, New York, NY, USA, 414-417.
38. Sakuyama K, Sasaki T, Ujiie S, Obata K, Mizugaki M, Ishikawa M, Hiratsuka M. Functional characterization of 17 CYP2D6 allelic variants (CYP2D6.2, 10, 14A-B, 18, 27, 36, 39, 47-51, 53-55, and 57). Drug Metab Dispos. 2008 Dec;36(12):2460-7. doi: 10.1124/dmd.108.023242. PubMed PMID: 18784265.
39. Marez D, Legrand M, Sabbagh N, Lo Guidice JM, Spire C, Lafitte JJ, Meyer UA, Broly F. Polymorphism of the cytochrome P450 CYP2D6 gene in a European population: characterization of 48 mutations and 53 alleles, their frequencies and evolution. Pharmacogenetics. 1997 Jun;7(3):193-202. PubMed PMID: 9241659.
40. Sachse C, Brockmöller J, Bauer S, Roots I. Cytochrome P450 2D6 variants in a Caucasian population: allele frequencies and phenotypic consequences. Am J Hum Genet. 1997 Feb;60(2):284-95. PubMed PMID: 9012401; PubMed Central PMCID: PMC1712396.
41. Desmet FO, Hamroun D, Lalande M, Collod-Béroud G, Claustres M, Béroud C. Human Splicing Finder: an online bioinformatics tool to predict splicing signals. Nucleic Acids Res. 2009 May;37(9):e67. doi: 10.1093/nar/gkp215. PubMed PMID: 19339519; PubMed Central PMCID: PMC2685110.
42. Wennerholm A, Johansson I, Hidestrand M, Bertilsson L, Gustafsson LL, IngelmanSundberg M. Characterization of the CYP2D6*29 allele commonly present in a black Tanzanian population causing reduced catalytic activity. Pharmacogenetics. 2001 Jul;11(5):417-27. Erratum in: Pharmacogenetics 2001 Nov;11(8):743. PubMed PMID: 11470994.
43. Dong C, Wei P, Jian X, Gibbs R, Boerwinkle E, Wang K, Liu X. Comparison and integration of deleteriousness prediction methods for nonsynonymous SNVs in whole exome sequencing studies. Hum Mol Genet. 2015 Apr 15;24(8):2125-37. doi: 10.1093/hmg/ddu733. Epub 2014 Dec 30. PubMed PMID: 25552646; PubMed Central PMCID: PMC4375422.
44. Lim ET, Würtz P, Havulinna AS, Palta P, Tukiainen T, Rehnström K, Esko T, Mägi R, Inouye M, Lappalainen T, et al. Sequencing Initiative Suomi (SISu) Project.. Distribution
and medical impact of loss-of-function variants in the Finnish founder population. PLoS Genet. 2014 Jul 31;10(7):e1004494. doi: 10.1371/journal.pgen.1004494. PubMed PMID: 25078778; PubMed Central PMCID: PMC4117444.
45. Peltonen L, Jalanko A, Varilo T. Molecular genetics of the Finnish disease heritage. Hum Mol Genet. 1999;8(10):1913-23. Review. PubMed PMID: 10469845.
46. Kere J. Human population genetics: lessons from Finland. Annu Rev Genomics Hum Genet. 2001;2:103-28. Review. PubMed PMID: 11701645.
47. Palo JU, Ulmanen I, Lukka M, Ellonen P, Sajantila A. Genetic markers and population history: Finland revisited. Eur J Hum Genet. 2009 Oct;17(10):1336-46. doi: 10.1038/ejhg.2009.53. Epub 2009 Apr 15. PubMed PMID: 19367325; PubMed Central PMCID: PMC2986642.
48. McCarroll SA, Hadnott TN, Perry GH, Sabeti PC, Zody MC, Barrett JC, Dallaire S, Gabriel SB, Lee C, Daly MJ, Altshuler DM; International HapMap Consortium.. Common deletion polymorphisms in the human genome. Nat Genet. 2006 Jan;38(1):86-92. PubMed PMID: 16468122.
49. Drögemöller BI, Wright GE, Niehaus DJ, Emsley R, Warnich L. Next-generation sequencing of pharmacogenes: a critical analysis focusing on schizophrenia treatment. Pharmacogenet Genomics. 2013 Dec;23(12):666-74. doi: 10.1097/FPC.00000000000000006. PubMed PMID: 24141736.
50. Wright GE, Carleton B, Hayden MR, Ross CJ. The global spectrum of protein-coding pharmacogenomic diversity. Pharmacogenomics J. 2016 Oct 25. doi: 10.1038/tpj.2016.77. [Epub ahead of print] PubMed PMID: 27779249.
51. Contreras AV, Monge-Cazares T, Alfaro-Ruiz L, Hernandez-Morales S, Miranda-Ortiz H, Carrillo-Sanchez K, Jimenez-Sanchez G, Silva-Zolezzi I. Resequencing, haplotype construction and identification of novel variants of CYP2D6 in Mexican Mestizos. Pharmacogenomics. 2011 May;12(5):745-56. doi: 10.2217/pgs.11.8. PubMed PMID: 21391885.
52. Beoris M, Amos Wilson J, Garces JA, Lukowiak AA. CYP2D6 copy number distribution in the US population. Pharmacogenet Genomics. 2016 Feb;26(2):96-9. doi: 10.1097/FPC.0000000000000188. PubMed PMID: 26551314; PubMed Central PMCID: PMC4704658.
53. Aklillu E, Persson I, Bertilsson L, Johansson I, Rodrigues F, Ingelman-Sundberg M. Frequent distribution of ultrarapid metabolizers of debrisoquine in an ethiopian population carrying duplicated and multiduplicated functional CYP2D6 alleles. J Pharmacol Exp Ther. 1996 Jul;278(1):441-6. PubMed PMID: 8764380.
54. Bertilsson L, Dahl ML, Dalén P, Al-Shurbaji A. Molecular genetics of CYP2D6: clinical relevance with focus on psychotropic drugs. Br J Clin Pharmacol. 2002 Feb;53(2):111-22. Review. PubMed PMID: 11851634; PubMed Central PMCID: PMC1874287.
55. Feng Y, Zhang Y, Ying C, Wang D, Du C. Nanopore-based fourth-generation DNA sequencing technology. Genomics Proteomics Bioinformatics. 2015 Feb;13(1):4-16. doi: 10.1016/j.gpb.2015.01.009. Epub 2015 Mar 2. Review. Erratum in: Genomics Proteomics Bioinformatics. 2015 Dec;13(6):383. Genomics Proteomics Bioinformatics. 2015 Jun;13(3):200-201. PubMed PMID: 25743089; PubMed Central PMCID: PMC4411503.
56. Wang D, Papp AC, Sun X. Functional characterization of CYP2D6 enhancer polymorphisms. Hum Mol Genet. 2015 Mar 15;24(6):1556-62. doi: 10.1093/hmg/ddu566. PubMed PMID: 25381333; PubMed Central PMCID: PMC4381757.

## Supplementary Information

Table S1. Population codes. 1000 Genomes Project population codes and descriptions for five super-populations and 26 sub-populations [15,16]. Table from Wendt, et al. 2017 [13].

| Super-Population (Code) | Sample Size | Population Code | Population Description | Sample Size |
| :---: | :---: | :---: | :---: | :---: |
| African (AFR) | 661 | YRI | Yoruba in Ibadan, Nigeria | 108 |
|  |  | LWK | Luhya in Webuye, Kenya | 99 |
|  |  | GWD | Gambian in Western Divisions in Gambia | 113 |
|  |  | MSL | Mende in Sierra Leone | 85 |
|  |  | ESN | Esan in Nigeria | 99 |
|  |  | ASW | American of African Ancestry in Southwest United States | 61 |
|  |  | ACB | African Caribbeans in Barbados | 96 |
| Ad Mixed American <br> (AMR) | 347 | MXL | Mexican Ancestry from Los Angeles, USA | 64 |
|  |  | PUR | Puerto Ricans from Puerto Rico | 104 |
|  |  | CLM | Colombians from Medellin, Colombia | 94 |
|  |  | PEL | Peruvians from Lima, Peru | 85 |
| East Asian (EAS) | 504 | CHB | Han Chinese in Beijing China | 103 |
|  |  | JPT | Japanese in Tokyo, Japan | 104 |
|  |  | CHS | Southern Han Chinese | 105 |
|  |  | CDX | Chinese Dai in Xishuangbanna, China | 93 |
|  |  | KHV | Kinh in Ho Chi Minh City, Vietnam | 99 |
| European (EUR) | 503 | CEU | Utah Residents (CEPH) with Northern and Western Ancestry | 99 |
|  |  | TSI | Toscani in Italia | 107 |
|  |  | FIN | Finnish in Finland | 99 |
|  |  | GBR | British in England and Scotland | 91 |
|  |  | IBS | Iberian Population in Spain | 107 |
| South Asian (SAS) | 489 | GIH | Gujarati Indian from Houston, Texas | 103 |
|  |  | PJL | Punjabi from Lahore, Pakistan | 96 |
|  |  | BEB | Bengali from Bangladesh | 86 |
|  |  | STU | Sri Lankan Tamil from the United Kingdom | 102 |
|  |  | ITU | Indian Telugu from the United Kingdom | 102 |

Table S2. CYP2D6 full-gene haplotypes aligned to reference genomes. Cytochrome p450 full-gene star allele string sequences (forward strand on the top, reverse strand on the bottom) aligned to and named according to the hg19 and hg38 reference genomes and GenBank accession M33388 sequence. Individual bases are colored for visual clarity; nucleotide numbers are in reference to the start codon of M33388 sequence for consistency with The Human Cytochrome P450 Allele Nomenclature Database nomenclature guidelines; amino acid changes are colored to indicate predicted severity of impact on resulting protein function [2838,42]; intronic regions between exons of the amino acid string sequence are dark grey; black boxes highlight differences between the four references sequences used; HCYPAND causal polymorphisms not observed in the 1000 Genomes Project are considered invariable relative to the hg19 reference genome. Supplementary Table 2 can be viewed on the publisher's website: https://link.springer.com/article/10.1007/s00414-017-1709-0.
 $\infty$


Haplotype Number
$\begin{array}{ll}\text { Not Damaging Intronic Site } & \text { i Synonymous AA } \\ \text { \&Premature Stop Codon } & \text { ミFrameshift INDEL }\end{array}$

Damaging Splice Site Possible Damaging Splice Site
Most Likely Damaging AA Change $\quad$ Damaging AA Change

Figure S1. CYP2D6 full-gene haplotype composition. Haplotype composition of 446 fullgene CYP2D6 star alleles aligned to GenBank accession M33388 (A), hg19 (B), and hg38 (C). Variant effect predictions described by Wendt, et al. [13] using Sort Intolerant From Tolerant [28-33], Polymorphism Phenotyping v2 [28,34,35], Protein Variant Effect Analyzer [36-38], and Human Splicing Finder [42].


Figure S2. Network analysis of CYP2D6 full-gene haplotypes observed more than once. Network analysis of CYP2D6 full-gene haplotypes 1 through 204. Haplotypes with global frequencies $\geq 1 \%$ are labeled, the size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of variants separating two haplotypes. Haplotypes observed once in the global population (haplotypes 205 through 446) were removed prior to network analysis.

CHAPTER 4

# Predicted Activity of UGT2B7, ABCB1, OPRM1, and COMT using full-gene haplotypes and their association with the CYP2D6-inferred metabolizer phenotype 

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Frank R Wendt
Antti Sajantila
Bruce Budowle


#### Abstract

The pharmacogene, CYP2D6, is commonly used to infer metabolizer phenotype of many marketed drugs and endogenous toxins in ante- and post-mortem patients but only represents the efficiency of phase 1 metabolism. Downstream metabolic enzymes encoded by UGT2B7, ABCB1, OPRM1, and COMT also have been implicated in variable individual response to drugs due to their activity at different stages of the tramadol ADME (absorption, distribution, metabolism, and excretion) process. While commonly studied as single genes using targeted genotyping approaches, a more comprehensive tramadol metabolism profile has not been evaluated. 1000 Genomes Project data for $U G T 2 B 7, A B C B 1, O P R M 1$, and $C O M T$ were used to characterize fullgene haplotypes and their effect on protein function using in-house excel-based workbooks, PopART, and TreeView. Population genetic summary statistics and intergenic analyses associated these haplotypes with full-gene CYP2D6-inferred metabolizer phenotype. The findings suggest that $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT may contribute to predicted metabolizer phenotype as opposed to relying solely on CYP2D6.


## Introduction

The cytochrome p450 family 2 , subfamily D , polypeptide 6 (CYP2D6) enzyme is responsible for phase I metabolism of approximately $30 \%$ of marketed drugs and endogenous toxins [1,2]. CYP2D6 is a highly variable pharmacogene with well documented allele distributions that vary by demography [3-6]. Constellations of individual single nucleotide (SNPs) or insertion/deletion (INDELs) polymorphisms in CYP2D6 define star $\left({ }^{*}\right)$ alleles (i.e. a haplotype [operationally defined by a set of SNPs]) which may be used to predict the metabolizer phenotype (e.g. poor [PM], intermediate [IM], extensive/normal [EM/NM] and ultrarapid [UM]) of an individual using their CYP2D6 diplotype (i.e. combination of two CYP2D6 * alleles) information and associated activity scores. These data have demonstrated value for guiding individualized prescription medication practices and even post-mortem investigations [7-10].

The CYP2D6-inferred metabolizer phenotype describes only one phase of the tramadol (T) ADME (absorption, distribution, metabolism, and excretion) process and does not explain all genotypic contribution of an individual's phenotypic expression [11]. Numerous polymorphisms in the downstream metabolic enzymes uridine diphosphate glucuronosyltransferase, family 1 , polypeptide B7 (UGT2B7), adenosine triphosphate (ATP) binding cassette, subfamily B, number 1 (ABCB1), opioid receptor mu 1 (OPRM1), and catechol-O-methyltransferase (COMT) also have been implicated in idiosyncratic response to drugs. These ADME proteins are less well characterized and typically are interrogated in single-gene studies that associate relatively few SNPs/INDELs to rate of drug metabolism and/or enzyme activity [12-17]. It has been demonstrated that combinatorial pharmacogenetic profiles (i.e., data from multiple genes) improved patient outcomes in response to antidepressants [18,19] and opiates [20]. Therefore, a higher confidence in predicting a metabolizer phenotype may be realized if information from
multiple enzymes in an ADME pathway, such as CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT, are included in the analysis. For example, a CYP2D6*4/CYP2D6*4 homozygote is considered a PM and may be prescribed a higher dose of pro-drug (e.g., T) to reach the therapeutic window. However, that same individual may harbor an $A B C B 1$ diplotype which confers decreased efflux of O-desmethyltramadol (M1, the primary active metabolite of T) across the blood brain barrier, enabling a relatively large concentration of M1 to reach OPRM1 and stimulate analgesia propagation. Ultimately, a patient with this pair of diplotypes at CYP2D6 and ABCB1 should experience the desired, and safe, degree of pain relief, but relying solely on CYP2D6 information for this patient would support increasing the tramadol dose which potentially could cause hyperalgesia.

While combinatorial studies have been performed, they rely on targeted genotyping approaches to interrogate a priori SNPs and/or INDELs [13,15,20-24]. Consequently, novel polymorphism(s) cannot be identified that refine estimates of enzyme activity [25]. Massively parallel sequencing (MPS) of the full gene region increases the potential to discover polymorphisms that are currently excluded from phenotype predictions [26].

Herein, the SNP and INDEL variant effect prediction data presented by Wendt, et al. [27] are expanded upon using the phased data of the 1000 Genomes Project [28]. Full-gene haplotypes of $U G T 2 B 7, A B C B 1, O P R M 1$, and $C O M T$ were characterized in self-reported healthy individuals. When compared to CYP2D6-predicted metabolizer phenotype for the same individuals [25], it was demonstrated that NMs by CYP2D6 genotyping may possess poorly active downstream metabolic enzymes. Logistic regression suggests that phenotype predictions using CYP2D6-inferences alone do not explain all phenotypic variability as there may be contribution from polymorphisms in UGT2B7, ABCB1, OPRM1, and COMT.

## Materials and Methods

Polymorphisms in the $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT gene regions, including introns, exons, $5^{\prime}$ and $3^{\prime}$ untranslated regions (UTRs), and promoters, were downloaded from Phase 3 of the 1000 Genomes Project and analyzed individually in 5 super- and 26 sub-populations (Table S1) according to Wendt, et al. [27]. Haplotypes for each gene were produced according to Table 1 and individual haplotypes are listed in Table S2. Certain polymorphisms characterized were removed from haplotype formation to simplify downstream analyses but capture meaningful levels of variation within each gene. Those excluded variants differ for each gene based on gene size, number of polymorphic sites within each gene, and the consensus variant effect prediction of each polymorphism. In general, polymorphisms that were not scored by Sort Intolerant From Tolerant (SIFT) [34-39], Polymorphisms Phenotyping v2 (PolyPhen-v2) [34,40,41], Protein Variant Effect Analyzer (PROVEAN) [42-44], or Human Splicing Finder (HSF) [45], were removed. Private mutations (SNPs or INDELs observed once in the 1000 Genomes Project) were included/excluded on a gene-by-gene basis. $A B C B 1$ was divided into four haplotype blocks based on Sai, et al. [30,31]. Herein, haplotype block ABCB1-Block-1 has been extended to include untranslated exon 1 (Figure 1).

Table 1. Haplotype production approach for $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT. Private mutations are defined as those observed once in the global population (all 2,504 1000 Genomes Project individuals).

| Gene | Total <br> Polymorphisms | Full-Gene Haplotypes | Processing Notes | Polymorphisms Removed | Polymorphisms Included | Final Haplotypes |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| UGT2B7 | 613 | 887 | Removal of private mutations except those predicted damaging or most likely damaging $[27,29]$ | 246 | 367 | 641 |
| ABCB1 | 5,986 | >3,000 | Removal of all unscored polymorphisms [27]; gene broken into haplotype blocks [30,31] | 5,310 | 676 Total (51 <br> Block 3; 511 <br> Block 2; 106 <br> Block 1; 8 Block <br> -1) | 98 Block 3; 754 Block 2; 208 Block 1; 9 Block -1 |
| OPRM1 | 6,831 | > 3,000 | Removal of all unscored polymorphisms [27] | 6,627 | 204 | 527 |
| COMT | 1,007 | 2,131 | Removal of all unscored polymorphisms [27] | 924 | 83 | 377 |



Figure 1. $A B C B 1$ haplotype blocks. Image modified from Integrative Genomics Viewer $[32,33]$ indicated chromosome 7 coordinates are relative to the hg19 reference genome.

Using in-house Excel-based workbooks, haplotypes were aligned to the hg19 and hg38 reference genomes. Haplotypes were named with the following nomenclature format: reference sequence (genome name)-community recognized star allele (if known)-list of polymorphism rs numbers, if known, and the base at each position. Note that within text haplotypes were referenced using numeric identifiers relative to their frequency in the global population of all 2,504 1000 Genomes Project individuals (Table S2).

Population genetic summary statistics for five super- and 26 sub-populations, including haplotype and diplotype frequencies (analogous to allele and genotype frequencies), observed $\left(\mathrm{H}_{\mathrm{o}}\right)$
and expected $\left(\mathrm{H}_{\mathrm{e}}\right)$ heterozygosities, pairwise genetic distances, and tests for detection of departures from Hardy Weinberg Equilibrium (HWE) and linkage disequilibrium were performed using Genetic Data Analysis (GDA) [46] and the RStudio® package ggplot2 [47]. TreeView Version 1.6.6 Build $7601[48,49]$ was used to create phylogenetic trees; haplotype network analyses were performed using Population Analysis with Reticulate Trees (PopART) using the ancestral parsimony setting [50].

Enzyme activity was predicted using commonly typed and previously described polymorphisms for each gene [13,17,29-31,51-53]. Due to lack of empirical data for each polymorphism, additional damaging or most likely damaging polymorphisms in a gene were assumed to completely eliminate enzyme function. Logistic regression was used to explore possible relationships between the well-characterized CYP2D6-inferred metabolizer phenotype, represented as an activity score (a qualitative measure of phenotype derived from the activity conferred by each * allele an individual carries [54]) and the predicted activity of UGT2B7, $A B C B 1, O P R M 1$, and COMT. These data were then used to interpret the potential utility of a combinatorial pharmacogenetic profile.

## Results and Discussion

## UGT2B7, ABCB1, OPRM1, and COMT

A total of $641,98,754,208,9,527$, and 377 string sequences were observed for $U G T 2 B 7$, ABCB1-Block 3, ABCB1-Block 2, ABCB1-Block 1, ABCB1-Block -1, OPRM1, and COMT, respectively (Table 1 and Figure 2). ABCB1-Block 3 haplotype 1, ABCB1-Block 2 haplotype 191, ABCB1-Block 1 haplotype 8, ABCB1-Block -1 haplotype 3, and COMT haplotype 1, respectively, were identical to the hg19/hg38 reference genomes. No UGT2B7 and OPRM1 haplotypes were
identical to the hg19/hg38 reference sequences. A majority of haplotypes were observed once in the global population so the average global frequency of haplotypes for each gene was quite low ( $0.00156 \pm 0.00690$ for $U G T 2 B 7,0.0102 \pm 0.0566$ for ABCB1-Block 3, $0.00133 \pm 0.00699$ for ABCB1-Block 2, $0.00481 \pm 0.0243$ for ABCB1-Block $1,0.111 \pm 0.222$ for ABCB1-Block -1 , $0.00190 \pm 0.00873$ for $O P R M 1$, and $0.00265 \pm 0.00900$ for COMT). UGT2B7 haplotypes 1-20, ABCB1-Block 3 haplotypes 1-7, ABCB1-Block 2 haplotypes 1-17, ABCB1-Block 1 haplotypes 116, ABCB1-Block -1 haplotypes 1-3, OPRM1 haplotypes 1-18, and COMT haplotypes 1-21 had global alleles frequencies $\geq 1 \%$ (Figure 2), with average frequencies of $0.0284 \pm 0.0278$ for UGT2B7, $0.127 \pm 0.186$ for ABCB1-Block 3, $0.0293 \pm 0.0371$ for ABCB1-Block 2, $0.0516 \pm 0.0748$ for ABCB1-Block 1, $0.331 \pm 0.229$ for ABCB1-Block $-1,0.0371 \pm 0.0311$ for OPRM1, and 0.0298 $\pm 0.0255$ for COMT.


Figure 2. Haplotype frequencies for $U G T 2 B 7$ (A), ABCB1-Block 3 (B), ABCB1-Block 2 (C), ABCB1-Block 1 (D), ABCB1-Block-1 (E), OPRM1 (F), and COMT (G) in five super-populations (African [AFR; circles], Admixed American [AMR; horizontal lines], East Asian [EAS; squares], European [EUR; diamonds], and South Asian [SAS; triangles]).

Variant compositions for the most common haplotypes of each gene and for all haplotypes are displayed in Figures 3 and S1, respectively. Empirical data are not present for the large number of haplotypes observed so for the descriptive purposes of this work, the presence of one damaging, or most likely damaging [27,34-45], polymorphism in the haplotype is considered sufficient to decrease enzyme function. The average number of polymorphisms per haplotype was $59.8 \pm 27.6$ for $U G T 2 B 7,3.56 \pm 1.01$ for ABCB1-Block $-1,4.50 \pm 1.97$ for ABCB1-Block 1, $16.5 \pm 7.00$ for ABCB1-Block 2, $3.08 \pm 1.21$ for ABCB1-Block 3, $11.3 \pm 2.62$ for $O P R M 1$, and $4.89 \pm 1.99$ for COMT. Due to limited studies of the polymorphic nature of these four genes and inclusion of additional interrogated regions, none of the observed sequences herein were identical to previously reported star $\left(^{*}\right)$ alleles (a haplotype of polymorphisms along the length of the gene region) for UGT2B7, ABCB1, OPRM1, and COMT. It should be noted that a substantial number of SNPs/INDELs found in each haplotype (Figures 3 and S1) are found in intronic or $5^{\prime}$ and $3^{\prime}$ untranslated regions and may have no individual impact on protein function but my play roles in regulating splice variation, rate of transcription, or have epistatic effects.


Figure 3. Haplotype composition of 19, 3, 16, 17, 7, 18, and 21 haplotypes in UGT2B7 (A), ABCB1-Block -1 (B), ABCB1-Block 1 (B), ABCB1-Block 2 (B), ABCB1-Block 3 (B), OPRM1 $(\mathrm{C})$, and $\operatorname{COMT}(\mathrm{D})$, respectively, with global frequencies $\geq 1 \%$. Variant effect predictions presented by Wendt, et al. [27] using Sort Intolerant From Tolerant [34-39], Polymorphism Phenotyping v2 [34,40,41], Protein Variant Effect Analyzer [42-44], and Human Splicing Finder [45].

Network analysis was performed to determine the relatedness of two sets of haplotypes for each gene of interest: (1) haplotypes having >1\% global haplotype frequency (Figure 4), and (2) haplotypes observed more than once in the 1000 Genomes Project dataset (Figure S2). Networks for UGT2B7, ABCB1-Block 3, ABCB1-Block 2, and ABCB1-Block-1 haplotypes (Figure S2) appear to have more clearly defined haplotype relationships, less looping (multiple haplotypes may have multiple relationships with nearby haplotypes), and/or less reticulation (the degree of "webbing" in the network) than those of OPRM1 and COMT. This observation is possibly attributable to the relatively few number of polymorphisms separating OPRM1 and COMT haplotypes or be an artifact of deleting private mutations which may sufficiently differentiate the
relationships between haplotypes; alternatively, the substantial reticulation in the OPRM1 and COMT haplotype networks might also suggest some degree of recombination between the regions of interest. Most major haplotypes in all four genes were observed in all five super-populations while many minor haplotypes were unique to one super-population, namely African (i.e., UGT2B7 haplotypes stemming from $U G T 2 B 7-\mathrm{H} 19)$. This observation may be due to population-specificity and/or sampling effects.


Figure 4. Network analysis of $U G T 2 B 7$ haplotypes 1-20 (A), ABCB1-Block 3 haplotypes 1-7 (B), $A B C B 1$-Block 2 haplotypes 1-17 (C), ABCB1-Block 1 haplotypes 1-16 (D), ABCB1-Block -1 haplotypes 1-9 (E), OPRMI haplotypes 1-18 (F), and COMT haplotypes 1-21 (G). The size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.

There were $1,414,225,1,530,567,17,1,219$, and 1,267 unique $U G T 2 B 7, A B C B 1$-Block 3, ABCB1-Block 2, ABCB1-Block 1, ABCB1-Block -1, OPRM1, and COMT diplotypes, respectively, observed across 2,504 individuals. The average global diplotype frequencies were $7.07 \times 10^{-4} \pm 0.00151$ for UGT2B7, $0.00444 \pm 0.0234$ for ABCB1-Block 3, $6.534 \times 10^{-4} \pm 0.00149$ for ABCB1-Block 2, $0.00176 \pm 0.00685$ for ABCB1-Block 1, $0.0588 \pm 0.125$ for ABCB1-Block -1, $8.20 \times 10^{-4} \pm 0.00211$ for $O P R M 1$, and $7.96 \times 10^{-4} \pm 0.00142$ for COMT. Population-specific diplotype frequencies are displayed in Figure S5. The average observed diplotype heterozygosity was $0.850 \pm 0.129,0.745 \pm 0.172,0.690 \pm 0.224,0.753 \pm 0.1700 .687 \pm 0.191$ for the African (AFR), Ad Mixed American (AMR), East Asian (EAS), European (EUR), and South Asian (SAS) super-populations, respectively. Prior to Bonferroni correction (p < 0.05), UGT2B7, OPRM1, and COMT deviated significantly from HWE expectations in all five, two (AFR and EAS), and one (AMR) super-populations, respectively. After Bonferroni correction (p < 0.00714), UGT2B7 and OPRM1 deviated significantly from HWE expectations in four (AMR, EAS, EUR, and SAS) and one (EAS) super-populations, respectively, out of the five total super-populations (Figure 5).


Figure 5. Observed and expected heterozygosity of $A B C B 1$-Block -1, $A B C B 1$-Block 1, $A B C B 1$ Block 2, ABCB1-Block 3, COMT, OPRM1, and UGT2B7 haplotypes in five super-populations (African [AFR] in solid circles; Admixed American [AMR] in solid triangles; East Asian [EAS] in squares; European [EUR] in plus signs; South Asian [SAS] in "X"-filled squares) and the 26 sub-populations within each super-population. The size of each data point represents the HardyWeinberg Equilibrium p-value for each population; labeled populations indicate significance after Bonferroni correction (p < 0.00714).

## Intergenic Analyses

Unrooted neighbor-joining trees (Figure S4) of super- and sub-populations using each gene individually ( $A B C B 1$ is a combination of all four haplotype blocks) tend to show separation more so of the AFR and EAS populations while the AMR, EAS, and SAS populations cluster closer together. Considering all five genes (Figure 6) the same super-population trend is seen. Generally, the sub-populations within each super-population were grouped closely together; however, the Gujarati Indian from Houston, Texas (GIH) and the Peruvians from Lima, Peru (PEL) populations plot separately from the group of AMR, EUR, and SAS sub-populations.


Figure 6. Neighbor-joining trees for five super- (A) and twenty-six sub-populations (B) in the 1000 Genomes Project using pairwise genetic distances based on CYP2D6 [25], UGT2B7, ABCB1Block 3, ABCB1-Block 2, ABCB1-Block 1, ABCB1-Block -1, OPRM1, and COMT haplotype assignments.

Intergenic pairwise LD was tested using full-gene haplotypes for CYP2D6 [25], UGT2B7, ABCB1-Block 3, ABCB1-Block 2, ABCB1-Block 1, ABCB1-Block -1, OPRM1, and COMT to identify associations between metabolically relevant genes. Prior to Bonferroni correction (p< 0.05 ) and after removal of significant associations between $A B C B 1$ haplotype blocks, there were ten, 16 , eight, five, and ten significant pairwise LDs in the AFR, AMR, EAS, EUR, and SAS superpopulations, respectively (Figures 7 and S5). After Bonferroni correction (p $<0.00179$ ), there were six, five, one, two, and one significant pairwise LDs in the AFR, AMR, EAS, EUR, and SAS super-populations, respectively, most of which contain CYP2D6 and an additional downstream metabolic enzyme. The AFR super-population exhibited more LDs than any other superpopulation (though the significant correlations are weak [average Pearson's $r=0.0181$ ]) and those increased LDs are detected in the AFR sub-populations as well. These data are contrary to the expectations of lower LD in AFR populations compared with other population groups [55] but were observed with the individual SNP data as well so this observation is not surprising [27]. However, the effect may be artifactual and possibly explained by the highly polymorphic nature of these genes in the AFR population which results in an overall low frequency of each haplotype (Figure 2). Consequently, a large number of diplotypes may be observed only once in the AFR super-population, making the comprised haplotypes appear to be in LD due to scant observations of each haplotype. When compressed to minimize the impact of rare diplotypes using the "collapse less-frequent alleles" function in GDA, significant LDs were observed between CYP2D6 and UGT2B7, ABCB1-Block -1, ABCB1-Block 1, ABCB1-Block 2, ABCB1-Block 3, OPRM1 and COMT, with Pearson's r-values ranging from -0.0562 to 0.0610 for AFR and -0.0903 to 0.129 for AMR. Though not observed across the whole ADME process, there were some significant LDs between CYP2D6 and other downstream enzymes in the EAS, EUR, and SAS populations as well.

Of particular interest are the significant pairwise LDs between CYP2D6/UGT2B7 (-0.0562 [AFR] to 0.0934 [AMR]) and CYP2D6/COMT ( -0.0902 [EUR] to 0.129 [AMR]) in all five superpopulations, which may represent associations between their functional impact. The COMT locus is found in a one megabase $(\mathrm{Mb})$ region of chromosome 22 with a relatively high average recombination rate $(2.40 \pm 1.56$ centimorgans $/ \mathrm{Mb}$ ) which may artificially inflate the LD pattern involving this locus [55-59]. These empirical data have not yet been explored and more research is needed to support whether an effect is real.


Figure 7. Heat maps of pairwise linkage disequilibrium p-values using CYP2D6 [25], UGT2B7, ABCB1-Block 3, ABCB1-Block 2, ABCB1-Block 1, ABCB1-Block -1, OPRM1, and COMT diplotype in the African (AFR), Admixed American (AMR), East Asian (EAS), European (EUR), and South Asian (SAS) super-populations.

Using previously identified genotype-phenotype data [13,17,29-31,51-53] and additional polymorphisms characterized by Wendt, et al. [27], the activities of UGT2B7, ABCB1, OPRM1 and COMT were predicted for each 1000 Genomes Project individual. When grouped by CYP2D6inferred metabolizer phenotype as a global cohort (2,504 self-reported healthy individuals), there was no association detected between metabolizer phenotype and the diplotype-predicted activity of the selected downstream metabolically-relevant enzymes. Positive and negative correlations were observed between COMT ( $\mathrm{p}=0.0223$ ) and UGT2B7 $(\mathrm{p}=0.0389)$ and CYP2D6 activities, respectively; however the variance at CYP2D6 activity score of 3 is quite large and may have
influenced the significance of this relationship (Figure 8A shaded regions). CYP2D6 activity score of 3 was only detected in one Toscani in Italia individual who carries one normally active and one increased activity $C Y P 2 D 6^{*}$ allele $\left(C Y P 2 D 6^{*} 1 / * 53\right)$. On the super-population level, there were more obvious trends, again between $U G T 2 B 7$ and COMT activities and the CYP2D6 activity score. Two super-populations showed significant associations between CYP2D6 and other enzyme activity: AMR and $U G T 2 B 7(\mathrm{p}=0.0340)$, and EAS and OPRM1 $(\mathrm{p}=0.0361)$. The remaining super-populations and genes did not exhibit significant associations between the CYP2D6-inferred metabolizer phenotype and diplotype-predicted downstream metabolic activity. Variant effect predictions [34-45] suggested that all 1000 Genomes Project self-reported healthy individuals possess an $A B C B 1$ diplotype that confers abnormal transporter activity. This observation may be misleading due to inaccuracies of the variant effect prediction programs used [27]. The functional consequences of individual $A B C B 1$ polymorphisms, the combined impact of multiple $A B C B 1$ polymorphisms, and the interaction between the effects of multiple polymorphisms in different genes are unavailable for comparison in this study but eventually will be needed to be empirically evaluated in affected, or drug-exposed, populations. If these observations are correct, the relative abundance of these splice-altering polymorphisms suggests that decreased ATP-dependent efflux efficiency may be the norm for self-reported healthy individuals. For example, rs2235027 has an alternate allele frequency of $0.517,0.516,0.383,0.509$, and 0.397 in the AFR, AMR, EAS, EUR, and SAS super-populations, respectively [27]. It can be hypothesized that affected, or drugexposed, individuals possess additional polymorphisms, or are enriched for those identified here, that further alter transporter function and play a role in the idiosyncratic drug response phenotype [60-63]. Also epistatic interactions between multiple ABCB1 SNPs/INDELs have been demonstrated to influence antiepileptic drug resistance [64]. Possibly a similar phenomenon is
observed in self-reported healthy individuals who have either 1) not been exposed to a drug with which the epistasis-associated phenotype is observed or 2 ) are expressing a low level phenotype below level of personal discomfort and reporting.


Figure 8. Regression analysis between CYP2D6 metabolizer phenotype [25] and predicted activity of downstream metabolic enzymes UGT2B7 (blue), ABCB1 (red), OPRM1 (green), and COMT (black) in the global population of 2,504 1000 Genomes Project individuals (A) and by super-populations (B). Predicted activity of each trans-acting metabolic enzyme is based on the sum of predicted haplotype activities and ranges from zero to two (inactive to normally active, respectively).

## Conclusions

Full-gene haplotypes of four genes encoding trans-acting T-metabolism proteins, UGT2B7, $A B C B 1, O P R M 1$, and COMT, were defined and characterized using substantially more polymorphic sites than previously employed in pharmacogenetic studies. In doing so, a large number of haplotypes were observed. The data presented demonstrate significant LDs between full-gene haplotypes of CYP2D6 and those of $U G T 2 B 7$ and $C O M T$; however, the functional effects of these findings need to be determined empirically. The relatively low frequency of each haplotype and associated diplotype may confound LD estimates simply because each haplotype was only observed in combination with one other haplotype. This study also proposed an extended ABCB1-Block -1, which included distal untranslated exon 1, and did not substantially increase acquired information over the truncated Block -1 reported by Sai, et al. [30,31]. Most individual haplotypes identified in this study were quite rare; however, relatively common haplotypes ( $\geq 1 \%$ global frequency) were identified which contain at least one damaging, or most likely damaging, polymorphism. It should be noted that copy number variation and CYP2D6/CYP2D7 gene conversion do occur in some individuals, primary UMs and may alter the presented LD and regression patterns [65]. These events were not considered herein for determining of CYP2D6 activity [11] due to the limitations of short read sequences that comprise 1000 Genomes Project data $[66,67]$. It is likely that ongoing developments in longer read sequencing technologies will provide more confident interpretation of structural variation from existing short-read sequences [68-71].

The variant effects of many polymorphisms included in these haplotype definitions have not been empirically evaluated by the pharmacogenetics/pharmacogenomics community. There are obvious limitations to using an algorithmic approach to variant effect [72]; however, the
predicted implications on phenotype should not be overlooked, instead they can be used to narrow the pool of potentially causal variants/haplotypes to explore empirically The inclusion of only selfreported healthy individuals in the 1000 Genomes Project means that additional functionallyrelevant haplotypes may be selected against being represented in this dataset. This limiting factor may impact the analyses performed above. It is likely that additional polymorphisms and/or specific haplotypes may be enriched, or selected for, in affected, or T-exposed, cohorts [73-75]. As such, there potentially are additional damaging haplotypes in these affected groups that have not been observed herein so a full-gene interrogation of affected cohorts may provide greater resolution to damaging haplotype population distribution. This possibility lends support to utilizing a comprehensive genotyping approach, such as relatively long-read MPS or continuousread nanopore technology in pharmacogenetic/pharmacogenomic interrogations [70,71,76].

Though limited to a large cohort of self-reported healthy individuals, associations between individual genes have been identified which may be clinically significant. Though slight, there is a relationship between the CYP2D6-inferred metabolizer phenotype and the diplotype-predicted activities of UGT2B7, ABCB1, OPRM1, and COMT. This association highlights the need for comprehensive functional evaluation of the impact of polymorphisms in all five genes, and/or combinations of two, three, or four of these genes, on drug metabolism in the same individuals. It is reasonable to hypothesize that empirical evaluation of these targets will reveal the advantage of combinatorial pharmacogenetic profiles in regards to increased patient efficacy and even assisting with medico-legal accident reconstruction [18-20]. Currently, these data remain relatively scarce in the literature. The data presented herein provide a basis to interrogate the highly polymorphic T-metabolism pathway, defining full-gene haplotypes for, and characterizing the association between, five pharmacogenes that can be utilized in clinical pharmacogenetic evaluations and post-
mortem molecular autopsy using gene-targeted MPS. It is likely that these data can be expanded upon, by interrogating additional ADME gene haplotypes, for broad applicability for predicting metabolizer phenotype following exposure to other opioid drugs.

## References

1. Ingelman-Sundberg M, Sim SC, Gomez A, Rodriguez-Antona C. Influence of cytochrome P450 polymorphisms on drug therapies: pharmacogenetic, pharmacoepigenetic and clinical aspects.Pharmacol Ther. 2007 Dec;116(3):496-526. Epub 2007 Oct 9. Review. PubMed PMID: 18001838.
2. Ingelman-Sundberg M. Genetic polymorphisms of cytochrome P450 2D6 (CYP2D6): clinical consequences, evolutionary aspects and functional diversity. Pharmacogenomics J. 2005;5(1):6-13. Review. PubMed PMID: 15492763.
3. Leathart JB, London SJ, Steward A, Adams JD, Idle JR, Daly AK. CYP2D6 phenotypegenotype relationships in African-Americans and Caucasians in Los Angeles. Pharmacogenetics. 1998 Dec;8(6):529-41. PubMed PMID: 9918137.
4. Bradford LD. CYP2D6 allele frequency in European Caucasians, Asians, Africans and their descendants. Pharmacogenomics. 2002 Mar;3(2):229-43. Review. PubMed PMID: 11972444.
5. Sistonen J, Fuselli S, Palo JU, Chauhan N, Padh H, Sajantila A. Pharmacogenetic variation at CYP2C9, CYP2C19, and CYP2D6 at global and microgeographic scales. Pharmacogenet Genomics. 2009 Feb;19(2):170-9. doi: 10.1097/FPC.0b013e32831ebb30. PubMed PMID: 19151603.
6. Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2017 Jan;19(1):69-76. doi: 10.1038/gim.2016.80. Epub 2016 Jul 7. PubMed PMID: 27388693; PubMed Central PMCID: PMC5292679.
7. Levo A, Koski A, Ojanperä I, Vuori E, Sajantila A. Post-mortem SNP analysis of CYP2D6 gene reveals correlation between genotype and opioid drug (tramadol) metabolite ratios in blood. Forensic Sci Int. 2003 Jul 29;135(1):9-15. PubMed PMID: 12893130.
8. Koren G, Cairns J, Chitayat D, Gaedigk A, Leeder SJ. Pharmacogenetics of morphine poisoning in a breastfed neonate of a codeine-prescribed mother. Lancet. 2006 Aug 19;368(9536):704. PubMed PMID: 16920476.
9. Koski A, Ojanperä I, Sistonen J, Vuori E, Sajantila A. A fatal doxepin poisoning associated with a defective CYP2D6 genotype. Am J Forensic Med Pathol. 2007 Sep;28(3):259-61. PubMed PMID: 17721180.
10. Sistonen J, Madadi P, Ross CJ, Yazdanpanah M, Lee JW, Landsmeer ML et al. Prediction of codeine toxicity in infants and their mothers using a novel combination of maternal genetic markers. Clin Pharmacol Ther. 2012 Apr;91(4):692-9. doi: 10.1038/clpt.2011.280. Epub 2012 Mar 7. PubMed PMID: 22398969.
11. Smith HS. Opioid metabolism. Mayo Clin Proc. 2009 Jul;84(7):613-24. doi: 10.1016/S0025-6196(11)60750-7. Review. PubMed PMID: 19567715; PubMed Central PMCID: PMC2704133.
12. Holthe M, Rakvåg TN, Klepstad P, Idle JR, Kaasa S, Krokan HE et al. Sequence variations in the UDP-glucuronosyltransferase 2B7 (UGT2B7) gene: identification of 10 novel single nucleotide polymorphisms (SNPs) and analysis of their relevance to morphine glucuronidation in cancer patients. Pharmacogenomics J. 2003;3(1):17-26. Erratum in: Pharmacogenomics J. 2003;3(4):248. PubMed PMID: 12629580.
13. Campa D, Gioia A, Tomei A, Poli P, Barale R. Association of ABCB1/MDR1 and OPRM1 gene polymorphisms with morphine pain relief. Clin Pharmacol Ther. 2008 Apr;83(4):559-66. Epub 2007 Sep 26. PubMed PMID: 17898703.
14. Chung JY, Cho JY, Yu KS, Kim JR, Lim KS, Sohn DR et al. Pharmacokinetic and pharmacodynamic interaction of lorazepam and valproic acid in relation to UGT2B7 genetic polymorphism in healthy subjects. Clin Pharmacol Ther. 2008 Apr;83(4):595-600. Epub 2007 Aug 8. PubMed PMID: 17687269.
15. Fujita K, Ando Y, Yamamoto W, Miya T, Endo H, Sunakawa Y et al. Association of UGT2B7 and ABCB1 genotypes with morphine-induced adverse drug reactions in Japanese patients with cancer. Cancer Chemother Pharmacol. 2010 Jan;65(2):251-8. doi: 10.1007/s00280-009-1029-2. PubMed PMID: 19466410.
16. Hodges LM, Markova SM, Chinn LW, Gow JM, Kroetz DL, Klein TE et al. Very important pharmacogene summary: ABCB1 (MDR1, P-glycoprotein). Pharmacogenet Genomics. 2011 Mar;21(3):152-61. doi: 10.1097/FPC.0b013e3283385a1c. PubMed PMID: 20216335; PubMed Central PMCID: PMC3098758.
17. Crist RC, Berrettini WH. Pharmacogenetics of OPRM1. Pharmacol Biochem Behav. 2014 Aug;123:25-33. doi: 10.1016/j.pbb.2013.10.018. Epub 2013 Nov 5. Review. PubMed PMID: 24201053; PubMed Central PMCID: PMC4010567.
18. Altar CA, Carhart J, Allen JD, Hall-Flavin D, Winner J, Dechairo B. Clinical Utility of Combinatorial Pharmacogenomics-Guided Antidepressant Therapy: Evidence from Three Clinical Studies. Mol Neuropsychiatry. 2015 Oct;1(3):145-55. doi: 10.1159/000430915. Epub 2015 Jul 31. PubMed PMID: 27606312; PubMed Central PMCID: PMC4996033.
19. Altar CA, Carhart JM, Allen JD, Hall-Flavin DK, Dechairo BM, Winner JG. Clinical validity: Combinatorial pharmacogenomics predicts antidepressant responses and healthcare utilizations better than single gene phenotypes. Pharmacogenomics J. 2015 Oct;15(5):443-51. doi: $10.1038 /$ tpj.2014.85. Epub 2015 Feb 17. PubMed PMID: 25686762.
20. Bastami S, Gupta A, Zackrisson AL, Ahlner J, Osman A, Uppugunduri S. Influence of UGT2B7, OPRM1 and ABCB1 gene polymorphisms on postoperative morphine consumption.

Basic Clin Pharmacol Toxicol. 2014 Nov;115(5):423-31. doi: 10.1111/bcpt.12248. Epub 2014 May 19. PubMed PMID: 24703092.
21. Handoko HY, Nyholt DR, Hayward NK, Nertney DA, Hannah DE, Windus LC et al. Separate and interacting effects within the catechol-O-methyltransferase (COMT) are associated with schizophrenia. Mol Psychiatry. 2005 Jun;10(6):589-97. PubMed PMID: 15505638.
22. Bartošová O, Polanecký O, Perlík F, Adámek S, Slanař O. OPRM1 and ABCB1 polymorphisms and their effect on postoperative pain relief with piritramide. Physiol Res. 2015;64 Suppl 4:S521-7. PubMed PMID: 26681082.
23. Christoffersen DJ, Damkier P, Feddersen S, Möller S, Thomsen JL, Brasch-Andersen C et al. The ABCB1, rs9282564, AG and TT Genotypes and the COMT, rs4680, AA Genotype are Less Frequent in Deceased Patients with Opioid Addiction than in Living Patients with Opioid Addiction. Basic Clin Pharmacol Toxicol. 2016 Oct;119(4):381-8. doi: 10.1111/bcpt.12602. Epub 2016 May 19. PubMed PMID: 27061230.
24. Sutiman N, Lim JS, Muerdter TE, Singh O, Cheung YB, Ng RC et al. Pharmacogenetics of UGT1A4, UGT2B7 and UGT2B15 and Their Influence on Tamoxifen Disposition in Asian Breast Cancer Patients. Clin Pharmacokinet. 2016 Oct;55(10):1239-50. doi: 10.1007/s40262-016-0402-7. PubMed PMID: 27098059.
25. Wendt FR, Sajantila A, Moura-Neto RS, Woerner AE, Budowle B. Full-gene haplotypes refine CYP2D6 metabolizer phenotype inferences. Int J Legal Med. 2017 Oct 26. doi: 10.1007/s00414-017-1709-0. [Epub ahead of print] PubMed PMID: 29075918.
26. Koch WH. Technology platforms for pharmacogenomic diagnostic assays. Nat Rev Drug Discov. 2004 Sep;3(9):749-61. Review. PubMed PMID: 15340385.
27. Wendt FR, Pathak G, Sajantila A, Chakraborty R, Budowle B. Global genetic variation of select opiate metabolism genes in self-reported healthy individuals. Pharmacogenomics J. 2017 Apr 11. doi: 10.1038/tpj.2017.13. [Epub ahead of print] PubMed PMID: 28398354.
28. http://www.internationalgenome.org/faq/are-1000-genomes-variant-calls-phased/. Accessed 01FEB2017.
29. UGT Nomenclature Committee. UGT Alleles Nomenclature Home Page. June 2005. http://www.ugtalleles.ulacal.ca, Accessed 20FEB2017.
30. Sai K, Itoda M, Saito Y, Kurose K, Katori N, Kaniwa N et al. Genetic variations and haplotype structures of the ABCB1 gene in a Japanese population: an expanded haplotype block covering the distal promoter region, and associated ethnic differences. Ann Hum Genet. 2006 Sep;70(Pt 5):605-22. PubMed PMID: 16907707.
31. Sai K, Kaniwa N, Itoda M, Saito Y, Hasegawa R, Komamura K et al. Haplotype analysis of ABCB1/MDR1 blocks in a Japanese population reveals genotype-dependent renal clearance of irinotecan. Pharmacogenetics. 2003 Dec;13(12):741-57. PubMed PMID: 14646693.
32. Robinson JT, Thorvaldsdóttir H, Winckler W et al. Integrative genomics viewer. Nat Biotechnol. 2011 Jan;29(1):24-6. doi: 10.1038/nbt.1754. PubMed PMID: 21221095; PubMed Central PMCID: PMC3346182.
33. Thorvaldsdóttir H, Robinson JT, Mesirov JP. Integrative Genomics Viewer (IGV): high performance genomics data visualization and exploration. Brief Bioinform. 2013 Mar;14(2):178-92. doi: 10.1093/bib/bbs017. Epub 2012 Apr 19. PubMed PMID: 22517427; PubMed Central PMCID: PMC3603213.
34. McLaren W, Gil L, Hunt SE, Riat HS, Ritchie GR, Thormann A, Flicek P, Cunningham F. The Ensembl Variant Effect Predictor. Genome Biol. 2016 Jun 6;17(1):122. doi: 10.1186/s13059-016-0974-4. PubMed PMID: 27268795; PubMed Central PMCID: PMC4893825.
35. Kumar P, Henikoff S, Ng PC. Predicting the effects of coding non-synonymous variants on protein function using the SIFT algorithm. Nat Protoc. 2009;4(7):1073-81. doi: 10.1038/nprot.2009.86. Epub 2009 Jun 25. PubMed PMID: 19561590.
36. Ng PC, Henikoff S. Predicting the effects of amino acid substitutions on protein function. Annu Rev Genomics Hum Genet. 2006;7:61-80. Review. PubMed PMID: 16824020.
37. Ng PC, Henikoff S. SIFT: Predicting amino acid changes that affect protein function. Nucleic Acids Res. 2003 Jul 1;31(13):3812-4. PubMed PMID: 12824425; PubMed Central PMCID: PMC168916.
38. Ng PC, Henikoff S. Accounting for human polymorphisms predicted to affect protein function. Genome Res. 2002 Mar;12(3):436-46. PubMed PMID: 11875032; PubMed Central PMCID: PMC155281.
39. Ng PC, Henikoff S. Predicting deleterious amino acid substitutions. Genome Res. 2001 May;11(5):863-74. PubMed PMID: 11337480; PubMed Central PMCID: PMC311071.
40. Adzhubei IA, Schmidt S, Peshkin L, Ramensky VE, Gerasimova A, Bork P, Kondrashov AS, Sunyaev SR. A method and server for predicting damaging missense mutations. Nat Methods. 2010 Apr;7(4):248-9. doi: 10.1038/nmeth0410-248. PubMed PMID: 20354512; PubMed Central PMCID: PMC2855889.
41. Adzhubei I, Jordan DM, Sunyaev SR. Predicting functional effect of human missense mutations using PolyPhen-2. Curr Protoc Hum Genet. 2013 Jan;Chapter 7:Unit7.20. doi: 10.1002/0471142905.hg0720s76. PubMed PMID: 23315928; PubMed Central PMCID: PMC4480630.
42. Choi Y, Sims GE, Murphy S, Miller JR, Chan AP. Predicting the functional effect of amino acid substitutions and indels. PLoS One. 2012;7(10):e46688. doi: 10.1371/journal.pone.0046688. Epub 2012 Oct 8. PubMed PMID: 23056405; PubMed Central PMCID: PMC3466303.
43. Choi Y, Chan AP. PROVEAN web server: a tool to predict the functional effect of amino acid substitutions and indels. Bioinformatics. 2015 Aug 15;31(16):2745-7. doi: 10.1093/bioinformatics/btv195. Epub 2015 Apr 6. PubMed PMID: 25851949; PubMed Central PMCID: PMC4528627.
44. Choi Y (2012) A Fast Computation of Pairwise Sequence Alignment Scores Between a Protein and a Set of Single-Locus Variants of Another Protein. In Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine (BCB '12). ACM, New York, NY, USA, 414-417.
45. Desmet FO, Hamroun D, Lalande M, Collod-Béroud G, Claustres M, Béroud C. Human Splicing Finder: an online bioinformatics tool to predict splicing signals. Nucleic Acids Res. 2009 May;37(9):e67. doi: 10.1093/nar/gkp215. PubMed PMID: 19339519; PubMed Central PMCID: PMC2685110
46. Weir, BS. 1996. Genetic Data Analysis. 2nd ed. Sinauer Associates, Sunderland, Massachusetts. 376 pages.
47. Wickham, H. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2009.
48. Page, RDM. 1996. TREEVIEW: An application to display phylogenetic trees on personal computers. Computer Applications in the Biosciences 12: 357-358.
49. TreeView Version $\quad 1.6 .6 \quad$ Build 7601. http://taxonomy.zoology.gla.ac.uk/rod/treeview/treeview_manual.html\#citing_treeview
50. Leigh J, Bryant D, Steel M. Population Analysis with Reticulate Trees (PopART). http://popart.otago.ac.nz
51. Xin L, Wang ZJ. Bioinformatic analysis of the human mu opioid receptor (OPRM1) splice and polymorphic variants. AAPS PharmSci. 2002;4(4):E23. PubMed PMID: 12645995; PubMed Central PMCID: PMC2751312.
52. Rakvåg TT, Klepstad P, Baar C, Kvam TM, Dale O, Kaasa S et al. The Val158Met polymorphism of the human catechol-O-methyltransferase (COMT) gene may influence morphine requirements in cancer pain patients. Pain. 2005 Jul;116(1-2):73-8. PubMed PMID: 15927391.
53. Takigawa H, Kowa H, Nakashima K. No associations between five polymorphisms in COMT gene and migraine. Acta Neurol Scand. 2017 Feb;135(2):225-230. doi: 10.1111/ane.12583. Epub 2016 Mar 14. PubMed PMID: 26988620.
54. Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS. The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther. 2008 Feb;83(2):234-42. Epub 2007 Oct 31. PubMed PMID: 17971818.
55. Campbell MC, Tishkoff SA. African genetic diversity: implications for human demographic history, modern human origins, and complex disease mapping. Annu Rev Genomics Hum Genet. 2008;9:403-33. doi: 10.1146/annurev.genom.9.081307.164258. Review. PubMed PMID: 18593304; PubMed Central PMCID: PMC2953791.
56. Serre D, Nadon R, Hudson TJ. Large-scale recombination rate patterns are conserved among human populations. Genome Res. 2005 Nov;15(11):1547-52. PubMed PMID: 16251464; PubMed Central PMCID: PMC1310642.
57. Broman KW, Murray JC, Sheffield VC, White RL, Weber JL. Comprehensive human genetic maps: individual and sex-specific variation in recombination. Am J Hum Genet. 1998 Sep;63(3):861-9. PMID: 9718341; PMC: PMC1377399
58. Dib C, Fauré S, Fizames C, Samson D, Drouot N, Vignal A, Millasseau P, Marc S, Hazan J, Seboun E et al. A comprehensive genetic map of the human genome based on 5,264 microsatellites. Nature. 1996 Mar 14;380(6570):152-4. PMID: 8600387
59. Kong A, Gudbjartsson DF, Sainz J, Jonsdottir GM, Gudjonsson SA, Richardsson B, Sigurdardottir S, Barnard J, Hallbeck B, Masson G et al. A high-resolution recombination map of the human genome. Nat Genet. 2002 Jul;31(3):241-7. PMID: 12053178
60. Levran O, O'Hara K, Peles E, Li D, Barral S, Ray B et al. ABCB1 (MDR1) genetic variants are associated with methadone doses required for effective treatment of heroin dependence. Hum Mol Genet. 2008 Jul 15;17(14):2219-27. doi: 10.1093/hmg/ddn122. Epub 2008 Apr 17. PubMed PMID: 18424454; PubMed Central PMCID: PMC2599947.
61. Fuselli S, de Filippo C, Mona S, Sistonen J, Fariselli P, Destro-Bisol G et al. Evolution of detoxifying systems: the role of environment and population history in shaping genetic diversity at human CYP2D6 locus. Pharmacogenet Genomics. 2010 Aug;20(8):485-99. doi: 10.1097/FPC.0b013e32833bba25. PubMed PMID: 20520586.
62. Hung CC, Chiou MH, Teng YN, Hsieh YW, Huang CL, Lane HY. Functional Impact of ABCB1 Variants on Interactions between P-Glycoprotein and Methadone. Quintas LEM, ed. PLoS ONE. 2013;8(3):e59419. doi:10.1371/journal.pone.0059419.
63. Yuferov V, Levran O, Proudnikov D, Nielsen DA, Kreek MJ. Search for genetic markers and functional variants involved in the development of opiate and cocaine addiction and treatment. Ann N Y Acad Sci. 2010 Feb;1187:184-207. doi: 10.1111/j.1749-6632.2009.05275.x. Review. PubMed PMID: 20201854; PubMed Central PMCID: PMC3769182.
64. Kim MK, Moore JH, Kim JK, Cho KH, Cho YW, Kim YS, Lee MC, Kim YO, Shin MH. Evidence for epistatic interactions in antiepileptic drug resistance. J Hum Genet. 2011 Jan;56(1):71-6. doi: 10.1038/jhg.2010.151. Epub 2010 Dec 2. PubMed PMID: 21124337.
65. McCarroll SA, Hadnott TN, Perry GH, Sabeti PC, Zody MC, Barrett JC, Dallaire S, Gabriel SB, Lee C, Daly MJ, Altshuler DM; International HapMap Consortium.. Common deletion
polymorphisms in the human genome. Nat Genet. 2006 Jan;38(1):86-92. PubMed PMID: 16468122.
66. Drögemöller BI, Wright GE, Niehaus DJ, Emsley R, Warnich L. Next-generation sequencing of pharmacogenes: a critical analysis focusing on schizophrenia treatment. Pharmacogenet Genomics. 2013 Dec;23(12):666-74. doi: 10.1097/FPC.0000000000000006. PubMed PMID: 24141736.
67. Wright GE, Carleton B, Hayden MR, Ross CJ. The global spectrum of protein-coding pharmacogenomic diversity. Pharmacogenomics J. 2016 Oct 25. doi: 10.1038/tpj.2016.77. [Epub ahead of print] PubMed PMID: 27779249.
68. Deamer DW, Akeson M. Nanopores and nucleic acids: prospects for ultrarapid sequencing. Trends Biotechnol. 2000 Apr; 18(4):147-51. Review. PubMed PMID: 10740260.
69. Kasianowicz JJ, Brandin E, Branton D, Deamer DW. Characterization of individual polynucleotide molecules using a membrane channel. Proc Natl Acad Sci U S A. 1996 Nov 26;93(24):13770-3. PubMed PMID: 8943010; PubMed Central PMCID: PMC19421.
70. Ammar R, Paton TA, Torti D, Shlien A, Bader GD. Long read nanopore sequencing for detection of HLA and CYP2D6 variants and haplotypes. F1000Res. 2015 Jan 21;4:17. doi: 10.12688/f1000research.6037.1. eCollection 2015. PubMed PMID: 25901276; PubMed Central PMCID: PMC4392832.
71. Lindberg MR, Schmedes SE, Hewitt FC, Haas JL, Ternus KL, Kadavy DR, Budowle B. A Comparison and Integration of MiSeq and MinION Platforms for Sequencing Single Source and Mixed Mitochondrial Genomes. PLoS One. 2016 Dec 9;11(12):e0167600. doi: 10.1371/journal.pone.0167600. eCollection 2016. PubMed PMID: 27936026; PubMed Central PMCID: PMC5147911.
72. Dong C, Wei P, Jian X, Gibbs R, Boerwinkle E, Wang K, Liu X. Comparison and integration of deleteriousness prediction methods for nonsynonymous SNVs in whole exome sequencing studies. Hum Mol Genet. 2015 Apr 15;24(8):2125-37. doi: 10.1093/hmg/ddu733. Epub 2014 Dec 30. PubMed PMID: 25552646; PubMed Central PMCID: PMC4375422.
73. Fallin D, Cohen A, Essioux L, Chumakov I, Blumenfeld M, Cohen D et al. Genetic analysis of case/control data using estimated haplotype frequencies: application to APOE locus variation and Alzheimer's disease. Genome Res. 2001 Jan;11(1):143-51. PubMed PMID: 11156623; PubMed Central PMCID: PMC311030.
74. Luo X, Zuo L, Kranzler H, Zhang H, Wang S, Gelernter J. Multiple OPR genes influence personality traits in substance dependent and healthy subjects in two American populations. Am J Med Genet B Neuropsychiatr Genet. 2008 Oct 5;147B(7):1028-39. doi: 10.1002/ajmg.b.30701. PubMed PMID: 18213616; PubMed Central PMCID: PMC3162230.
75. Mattei J, Parnell LD, Lai CQ, Garcia-Bailo B, Adiconis X, Shen J et al. Disparities in allele frequencies and population differentiation for 101 disease-associated single nucleotide polymorphisms between Puerto Ricans and non-Hispanic whites. BMC Genet. 2009 Aug 14;10:45. doi: 10.1186/1471-2156-10-45. PubMed PMID: 19682384; PubMed Central PMCID: PMC2734553.
76. Yang Y, Botton MR, Scott ER, Scott SA. Sequencing the CYP2D6 gene: from variant allele discovery to clinical pharmacogenetic testing. Pharmacogenomics. 2017 May;18(7):673-685. doi: 10.2217/pgs-2017-0033. Epub 2017 May 4. PubMed PMID: 28470112.

## Supplementary Information

Table S1. Population codes. 1000 Genomes Project population codes and descriptions for five super-populations and 26 sub-populations. Table from Wendt, et al. 2017 [27].

| $\begin{array}{l}\text { Super-Population } \\ \text { (Code) }\end{array}$ | $\begin{array}{l}\text { Sample } \\ \text { Size }\end{array}$ | $\begin{array}{l}\text { Population } \\ \text { Code }\end{array}$ | Population Description | Sample Size |
| :--- | :--- | :--- | :--- | :--- |
|  |  | YRI | Yoruba in Ibadan, Nigeria | 108 |
|  |  | LWK | $\begin{array}{l}\text { Luhya in Webuye, Kenya } \\ \text { GFrican (AFR) }\end{array}$ | Gambian in Western Divisions in Gambia |$]$| 99 |
| :--- |
|  |

Table S2. Short haplotype numbers, full-gene haplotype nomenclature, amino acid change, and predicted activity scores for UGT2B7, ABCB1-Block 3, ABCB1-Block 2, ABCB1-Block 1, ABCB1-Block -1, OPRM1, and COMT relative to the hg19 and hg38 reference genomes. Table S2 can be viewed on the Forensic Science International: Genetics website for this article (https://www.fsigenetics.com/article/S1872-4973(17)30260-0/abstract).


Figure S1. Haplotype composition of $641,9,208,754,98,527$, and 377 haplotypes in UGT2B7 (A), ABCB1-Block-1 (B), ABCB1-Block 1 (B), ABCB1-Block 2 (B), ABCB1-Block 3 (B), OPRM1 (C), and COMT (D), respectively, with global frequencies $\geq 1 \%$. Variant effect predictions presented by Wendt, et al. 2017 [27] using Sort Intolerant From Tolerant [34-39], Polymorphism Phenotyping v2 [34,40,41], Protein Variant Effect Analyzer [42-44], and Human Splicing Finder [45].


Figure S1 (continued). Haplotype composition of 641, 9, 208, 754, 98, 527, and 377 haplotypes in UGT2B7 (A), ABCB1-Block -1 (B), ABCB1-Block 1 (B), ABCB1-Block 2 (B), ABCB1-Block 3 (B), OPRM1 (C), and COMT (D), respectively, with global frequencies $\geq 1 \%$. Variant effect predictions presented by Wendt, et al. 2017 [27] using Sort Intolerant From Tolerant [34-39], Polymorphism Phenotyping v2 [34,40,41], Protein Variant Effect Analyzer [42-44], and Human Splicing Finder [45].


Figure S2. Network analysis of haplotypes observed more than once in the global population for UGT2B7 (haplotypes 1-285; A), ABCB1-Block 3 (haplotypes 1-53; B), ABCB1-Block 2 (haplotypes 1-271; C), ABCB1-Block 1 (haplotypes 1-102; D), OPRM1 (haplotypes 1-223; E), and COMT (haplotypes 1-215; F). Haplotypes with global frequencies $\geq 1 \%$ are labeled, the size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.


Figure S2 (continued). Network analysis of haplotypes observed more than once in the global population for UGT2B7 (haplotypes 1-285; A), ABCB1-Block 3 (haplotypes 1-53; B), ABCB1Block 2 (haplotypes 1-271; C), ABCB1-Block 1 (haplotypes 1-102; D), OPRM1 (haplotypes 1-223; E), and COMT (haplotypes 1-215; F). Haplotypes with global frequencies $\geq 1 \%$ are labeled, the size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.


Figure S2 (continued). Network analysis of haplotypes observed more than once in the global population for UGT2B7 (haplotypes 1-285; A), ABCB1-Block 3 (haplotypes 1-53; B), ABCB1Block 2 (haplotypes 1-271; C), ABCB1-Block 1 (haplotypes 1-102; D), OPRM1 (haplotypes 1-223; E), and COMT (haplotypes 1-215; F). Haplotypes with global frequencies $\geq 1 \%$ are labeled, the size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.


Figure S2 (continued). Network analysis of haplotypes observed more than once in the global population for $U G T 2 B 7$ (haplotypes 1-285; A), ABCB1-Block 3 (haplotypes 1-53; B), ABCB1Block 2 (haplotypes 1-271; C), ABCB1-Block 1 (haplotypes 1-102; D), OPRM1 (haplotypes 1-223; E), and COMT (haplotypes 1-215; F). Haplotypes with global frequencies $\geq 1 \%$ are labeled, the size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.


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Figure S2 (continued). Network analysis of haplotypes observed more than once in the global population for UGT2B7 (haplotypes 1-285; A), ABCB1-Block 3 (haplotypes 1-53; B), ABCB1Block 2 (haplotypes 1-271; C), ABCB1-Block 1 (haplotypes 1-102; D), OPRM1 (haplotypes 1-223; E), and COMT (haplotypes 1-215; F). Haplotypes with global frequencies $\geq 1 \%$ are labeled, the size of each circle is proportional to the global frequency of each haplotype, segments within each circle are proportional to the super-population haplotype frequency, and lines connecting circles are dashed with the number of mutations separating two haplotypes.


Figure S3. $U G T 2 B 7$ (A), ABCB1-Block 3 (B), ABCB1-Block 2 (C), ABCB1-Block 1 (D), ABCB1Block -1 (E), OPRM1 (F), and COMT (F) diplotype frequencies in the African (AFR), Admixed American (AMR), East Asian (EAS), European (EUR), and South Asian (SAS) super-populations. The x - and y - axes are the first and second haplotype number, respectively, of and individual diplotype plotted on a $\log 10$ scale; the size and color of each circle is proportional to the frequency of that diplotype with larger, bright data points indicating more frequent diplotypes.


Figure $\mathbf{S 3}$ (continued). UGT2B7 (A), ABCB1-Block 3 (B), ABCB1-Block 2 (C), ABCB1-Block 1 (D), ABCB1-Block-1 (E), OPRM1 (F), and COMT (F) diplotype frequencies in the African (AFR), Admixed American (AMR), East Asian (EAS), European (EUR), and South Asian (SAS) superpopulations. The $x$ - and $y$ - axes are the first and second haplotype number, respectively, of and individual diplotype plotted on a $\log 10$ scale; the size and color of each circle is proportional to the frequency of that diplotype with larger, bright data points indicating more frequent diplotypes.


Figure $\mathbf{S 3}$ (continued). UGT2B7 (A), ABCB1-Block 3 (B), ABCB1-Block 2 (C), ABCB1-Block 1 (D), ABCB1-Block-1 (E), OPRM1 (F), and COMT (F) diplotype frequencies in the African (AFR), Admixed American (AMR), East Asian (EAS), European (EUR), and South Asian (SAS) superpopulations. The $x$ - and $y$ - axes are the first and second haplotype number, respectively, of and individual diplotype plotted on a $\log 10$ scale; the size and color of each circle is proportional to the frequency of that diplotype with larger, bright data points indicating more frequent diplotypes.


Figure S4. Neighbor-joining trees for five super- and twenty-six sub-populations in the 1000 Genomes Project using pairwise genetic distances based on $U G T 2 B 7$ (A and B), ABCB1 (C and D), OPRM1 (E and F), and COMT (G and H) haplotype assignments. The $A B C B 1$ neighbor joining trees utilize diplotype information from all four haplotype blocks.

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Figure S4 (continued). Neighbor-joining trees for five super- and twenty-six sub-populations in the 1000 Genomes Project using pairwise genetic distances based on $U G T 2 B 7$ (A and B), ABCB1 ( C and D ), OPRM1 ( E and F ), and COMT ( G and H ) haplotype assignments. The $A B C B 1$ neighbor joining trees utilize diplotype information from all four haplotype blocks.


Figure S4 (continued). Neighbor-joining trees for five super- and twenty-six sub-populations in the 1000 Genomes Project using pairwise genetic distances based on $U G T 2 B 7$ (A and B), ABCB1 ( C and D ), OPRM1 ( E and F ), and COMT ( G and H ) haplotype assignments. The $A B C B 1$ neighbor joining trees utilize diplotype information from all four haplotype blocks.


Figure $\mathbf{S 4}$ (continued). Neighbor-joining trees for five super- and twenty-six sub-populations in the 1000 Genomes Project using pairwise genetic distances based on $U G T 2 B 7$ (A and B), ABCB1 ( C and D ), OPRM1 ( E and F ), and $C O M T$ ( G and H ) haplotype assignments. The $A B C B 1$ neighbor joining trees utilize diplotype information from all four haplotype blocks.


Figure S5. Heat maps of pairwise linkage disequilibrium p-values using CYP2D6 (Wendt FR, manuscript in review), UGT2B7, ABCB1-Block 3, ABCB1-Block 2, ABCB1-Block 1,ABCB1-Block -1, OPRM1, and COMT diplotype in twenty-six sub-populations from the 1000 Genomes Project.

## PART 3

## DESIGN AND IMPLEMENTATION OF

A MASSIVELY PARALLEL SEQUENCING LIBRARY<br>PREPARATION PANEL FOR<br>PREDICTING OPIATE METABOLIZER PHENOTYPE

## CHAPTER 5

# Supervised Classification of CYP2D6 Metabolizer Phenotype with Tramadol-Exposed Finns 

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Frank R Wendt
Nicole MM Novroski
Anna-Liina Rahikainen
Antti Sajantila
Bruce Budowle


#### Abstract

The cytochrome p450 family 2, subfamily D, polypeptide 6 (CYP2D6) may be used to infer the metabolizer phenotype (MP) of an individual as poor, intermediate, extensive/normal, or ultrarapid. MPs can guide prescription medication dosing to avoid idiosyncratic responses to a drug, such as tramadol, a commonly-prescribed synthetic opioid agonist used to treat moderate-to-severe post-operative pain. Application of CYP2D6 information has relied on long-range amplification of the locus and restriction enzyme digestion to detect single nucleotide variants (SNVs) associated with MPs. This process can be cumbersome and requires knowledge of genotype phase (i.e., the arrangement of alleles across genotypes indicating their position on the same DNA strand). Phase may be achieved using long-read DNA sequencing and/or computational methods; however, both can be error prone, which may make it difficult or impractical for implementation into clinical practice. CYP2D6 was interrogated in Finns using supervised machine learning and feature selection to identify a subset of SNVs indicative of MP and/or rate of tramadol O-demethylation (T:M1). A subset of 18 CYP2D6 SNVs could predict MP/T:M1 with up to $96.3 \%$ accuracy given phased data. These data indicate that phase contributes to classification accuracy when using CYP2D6 data. Of these 18 SNVs, three are novel loci putatively associated with T:M1. These findings may enable design of small multiplexes for easy clinical application of MP prediction.


## Introduction

Tramadol (T) is a synthetic opioid agonist and serotonin/norepinephrine reuptake inhibitor commonly used to relieve moderate to severe pain. ${ }^{1,2}$ Administered as a racemic mixture of $(+)$ and (-) enantiomers, tramadol is demethylated primarily by cytochrome p450 family 2 , subfamily D, polypeptide 6 (CYP2D6) to O-desmethyltramadol (M1). ${ }^{1,2}$ M1, (+) tramadol, and (-) tramadol contribute to the analgesic effect of the drug; ${ }^{3}$ however, CYP2D6 diplotypes have demonstrated significant influence on M1 pharmacokinetics (PK) in tramadol-treated patients. This variability in PK may result in idiosyncratic responses, including death. ${ }^{4,5}$

CYP2D6 is an extensively studied pharmacogene whose protein product is responsible for phase I metabolism of approximately $30 \%$ of marketed drugs, including tramadol, and a number of endogenous toxins. ${ }^{6-10}$ Current clinical uses of CYP2D6 genetic information rely on long-range amplification of the gene by the polymerase chain reaction (PCR) and subsequent restriction enzyme cleavage to detect the presence or absence of relevant polymorphisms or multiplexed SNaPshot assays. ${ }^{11-18}$ CYP2D6 genotype data are commonly arranged into star $\left(^{*}\right.$ ) alleles (i.e., a collection/haplotype of single nucleotide [SNPs] and/or insertion/deletion [INDELs] polymorphisms in the gene region) which, when combined into a diplotype (i.e., a genotype of two haplotypes), have been positively associated with the metabolizer phenotype (poor [PM], intermediate [IM], extensive/normal [EM/NM], and ultrarapid [UM]) of clinical patients and in post-mortem settings. ${ }^{19,20}$ Though they have predictive capabilities, CYP2D6 diplotypes currently require information beyond that of individual SNV genotypes, including their haplotype phase, predicted by either computational phasing or long-range PCR and subsequent long-read sequencing. ${ }^{21,22}$

There are several ways to phase data for related and unrelated cohorts, ${ }^{23}$ however, they have limitations. First, computational approaches are potentially limited by sample size, degree of sample relatedness, marker density, population substructure, and associated allele frequency differences. ${ }^{24,25}$ Large genes which currently rely on variant phase for phenotype analyses (e.g., pharmacogenes) are regularly analyzed as a haplotype, sometimes covering thousands of bases (see https://www.pharmacogenomics.pha.ulaval.ca/wp-content/uploads/2015/04/HAPUGT2B7.html). ${ }^{26-28}$ Haplotype analyses of these genes may be incorrect due to limitations of the computational/statistical phasing algorithm(s) used. Second, physically observed SNV phase may be achieved with long-read DNA sequencing chemistries which are theoretically a better solution to CYP2D6 and other pharmacogene studies; however, the read quality and error rates of shortread platforms are much better characterized and long-read and/or single-molecule chemistries are largely still under development. ${ }^{29-32}$

It is conceivable that a minimal set of maximally informative unphased SNV loci exist which can predict CYP2D6 MP with comparable accuracy as current approaches. By minimizing the number of loci required to predict a patient's response to a drug, the multiple amplification approach may be replaced by a multiplexed reaction whose products may serve as input for shortread massively parallel sequencing (MPS) chemistries or Sanger sequencing, which have been through extensive clinical and applied studies to characterize error rate and accuracy. ${ }^{33-36}$ An approach to pharmacogenetic predictions using CYP2D6, which does not rely on cumbersome restriction enzyme digestion and/or long-range amplification reactions, may prove advantageous in clinical application of pharmacogenetic data. Additionally, if predictions can be made in the absence of genotype phase, clinical utility of the CYP2D6 locus may be improved.

Herein, supervised machine learning was used to classify tramadol-exposed individuals from a Finnish population into their respective CYP2D6 MPs using a subset of maximally informative genotypes (i.e., selected features/attributes). Application of these data may reduce the need for long-range amplification of the $C Y P 2 D 6$ locus by focusing on a reduced subset of seven to 12 SNV loci that can predict the rate of tramadol O-demethylation and resulting MP category in clinical applications with accuracies as high as $96.3 \%$.

## Materials and Methods

## Subjects

A total of 208 whole blood samples were collected from medico-legal autopsies performed on Finnish individuals between 2001 and 2012 according to the ethical handling of human subjects review processes at the University of Helsinki and the University of North Texas Health Science Center (Institutional Review Board protocol \#2016-051) and stored on Whatman® ${ }^{\circledR}$ FTA® ${ }^{\circledR}$ cards (GE Healthcare Life Sciences, Marlborough, MA, USA). ${ }^{17}$ Note that sample size was determined by sample availability and not to achieve a specific predictive power.

## Toxicological Analysis

Summary statistics, including age and sex distribution, mean drug concentration information, and manner of death (MoD) distribution were performed in RStudio® version 1.0.136 (RStudio: Integrated Development for R. http://www.rstudio.com). Model-based clustering was performed in RStudio ${ }^{\circledR}$ using the package mclust version 5.2.3 ${ }^{37,38}$ and empirically-determined tramadol:O-desmethyltramadol (T:M1) ratios to define the most likely number of components (i.e., MPs) within the dataset, place each sample within one of the identified components based on
$\mathrm{T}: \mathrm{M} 1$ ratio, determine the error of sample assignment to a component, and display the distribution of each T:M1 ratio.

## DNA Extraction and Quantitation

DNA was extracted from FTA® cards using the QIAamp® DNA Blood Mini Kit (Qiagen, Hilden, Germany) according to the manufacturer's recommended protocol. ${ }^{39}$ Each DNA extract was eluted in a final DNA extract in approximately $100 \mu 1$ of elution buffer.

The quality and quantity of extracted DNA were determined using the Quantifiler ${ }^{\text {TM }}$ Trio DNA Quantification Kit (Applied Biosystems, Foster City, CA, USA) according to the manufacturer's recommended protocol. ${ }^{40}$ The samples used in this study have been stored on FTA cards and those maintained for long time periods may be subject to degradation and inhibitors, which may complicate downstream amplification of relatively long targets. ${ }^{17}$ DNA degradation and inhibition were evaluated using the degradation index (DI; ratio of small autosomal target DNA concentration to large autosomal target DNA concentration) and the internal PCR control cycle threshold (IPC C ${ }_{t}$ ) indicator, respectively. Possible inhibition was detected using an IPC $\mathrm{C}_{\mathrm{t}}$ threshold of 30, with sample IPC C $\mathrm{C}_{\mathrm{t}}$ values > 30 indicating an inhibited sample. DNA extracts also were quantified on the Qubit® 2.0 Fluorometer (Invitrogen, Carlsbad, CA, USA) with the Qubit® double-stranded DNA Broad Range Assay according to the manufacturer's recommended protocol. ${ }^{41}$ Qubit ${ }^{\circledR}$ quantification results were used to normalize all DNA extracts to $2.5 \mathrm{ng} / \mu \mathrm{l}$.

## CYP2D6 Long-PCR

CYP2D6, CYP2D6 duplications, and CYP2D7P/CYP2D6 hybrid genes (i.e., CYP2D6*13 and subtypes; see https://www.pharmvar.org/gene-support/Variation_CYP2D6.pdf) were
amplified using the KAPA LongRange HotStart PCR Kit (KAPA Biosystems, Inc., Wilmington, MA, USA) with the KAPA triplex reaction. The resulting PCR products were expected to be $\sim 6.6$ $\mathrm{kb}, \sim 3.5 \mathrm{~kb}$, and $\sim 5 \mathrm{~kb}$ (Fragments A, B, and H, respectively; Table 1). Amplification was performed in $25 \mu \mathrm{l}$ reaction volumes using 10 ng genomic DNA, 1X KAPA LongRange Buffer, $1.5 \mathrm{mM} \mathrm{MgCl}_{2}, 0.2 \mathrm{mM}$ each dNTP, 0.625 U KAPA LongRange HotStart DNA Polymerase, $5 \%$ DMSO, $0.5 \mu \mathrm{M}$ KAPA Fragment A Forward primer, $0.5 \mu \mathrm{M}$ KAPA Fragment A Reverse primer, $0.5 \mu \mathrm{M}$ KAPA Fragment B Forward primer, $0.5 \mu \mathrm{M}$ KAPA Fragment B Reverse primer, and 0.5 $\mu \mathrm{M}$ KAPA Fragment H Forward primer. PCR cycling included an initial denaturation at $95^{\circ} \mathrm{C}$ for 3 minutes followed by 35 cycles of denaturation at $95{ }^{\circ} \mathrm{C}$ for 15 seconds and annealing/extension at $68{ }^{\circ} \mathrm{C}$ for 7 minutes and 30 seconds. All PCR products were visualized using the Agilent 2200 TapeStation (Agilent Technologies, Waldbronn, Germany) with the Agilent 2200 Genomic DNA ScreenTape Assay using $10 \mu 1$ sample buffer and $1 \mu 1$ sample/ladder. PCR products were quantified using the Qubit 2.0 Fluorometer with the Qubit® double-stranded DNA Broad Range Assay according to the manufacturer's recommended protocol. ${ }^{41}$ All PCR products were normalized to $0.2 \mathrm{ng} / \mu \mathrm{l}$. Note that the CYP2D6 $* 5$ deletion was detected using the KAPA $* 5$ primer pair and internal control primers using the same reaction and cycling conditions described previously.

Table 1. Primer sequences (KAPA Biosystems, Inc.) used to amplify different structural variations of the CYP2D6 locus on chromosome 22.

| Primer Description | Sequence ( $\mathbf{5}^{\prime} \rightarrow \mathbf{3}^{\prime}$ ) | $\begin{gathered} \text { Expected } \\ \text { Product Size } \\ (k b) \\ \hline \end{gathered}$ | Description |
| :---: | :---: | :---: | :---: |
| Fragment A Forward | ATGGCAGCTGCCATACAATCCACCTG | 6.6 | Indicates presence of at least one wild type CYP2D6 allele, as determined by size. |
| Fragment A Reverse | CGACTGAGCCCTGGGAGGTAGGTAG |  |  |
| Fragment B Forward | CCATGGAAGCCCAGGACTGAGC | 3.5 | Indicates presence of at least one gene duplication. |
| Fragment B Reverse | CGGCAGTGGTCAGCTAATGAC |  |  |
| Fragment H Forward | TCCGACCAGGCCTTTCTACCAC | 5 | Indicates presence of at least one CYP2D7P/CYP2D6 hybrid |
| CYP2D6*5 Forward | CTCCAGCCTCCACCAGTCCAG | 2.9 | Indicates deletion of CYP2D6 |
| CYP2D6*5 Reverse | CAGGCATGAGCTAAGGCACCCAGAC |  |  |
| Internal Control Forward | GCATGCACAGCTCAGCACTGC | 3.8 | Indicates a successful PCR reaction |
| Internal Control Reverse | GCCACCCTGATGTCTCAGTTTCG |  |  |

## Library Preparation and Sequencing

One nanogram $(0.2 \mathrm{ng} / \mu \mathrm{l})$ of CYP2D6 triplex long-PCR product was used as input for Nextera XT (Illumina, Inc., San Diego, CA, USA) library preparation using enzymatic fragmentation and adapter ligation according to the manufacturer's recommended protocol. ${ }^{42}$ Library traces were spot-checked using the Agilent 2200 TapeStation with the Agilent 2200 High Sensitivity D1000 ScreenTape System using $2 \mu 1$ reaction buffer and $2 \mu \mathrm{l}$ sample/ladder. Positive and negative controls were included in the post-clean-up library check. Successfully prepared libraries were visualized as having broad size distribution from approximately 250 to 1250 bp . Pooled and normalized libraries were loaded into a MiSeq Reagent Kit v2 (500 cycles; $2 \times 250 \mathrm{bp}$ read length); sequencing was performed on the MiSeq (Illumina, Inc.) according to the manufacturer's recommended protocol. ${ }^{43}$ Note that PhiX ( 12.5 pM ) was included in all sequencing runs.

## Alignment, Variant Analysis, and Machine Learning

Fastq files were locally aligned to the hg19/GRCh37 reference genome using the BurrowsWheeler Aligner (BWA) mem command and the Sequence Alignment/Map Tools (SAMtools) view, sort, and index commands. ${ }^{44-46}$ The resulting sorted batch alignment/map (.sorted.bam) files were input for the Genome Analysis Toolkit (GATK). ${ }^{47}$ The resulting variant call format (.vcf) files were used as input for VCFtools, ${ }^{48}$ PLINK, ${ }^{49}$ Genome-wide Complex Trait Analysis (GCTA), ${ }^{50}$ and in-house Excel-based workbooks.

CYP2D6 locus phase was inferred using the IMPUTE2 ${ }^{51}$-phase command with reference to the hg19/GRCh37 genome. Phased loci recognized by the Pharmacogene Variation (PharmVar) Consortium Human Cytochrome P450 Allele Nomenclature database (see
https://www.pharmvar.org/gene/CYP2D6; accessed 16JAN2018) relevant for * allele assignment were analyzed using the CYP2D6 VCF Translator. ${ }^{52}$ Output from the translator was used to infer CYP2D6 * alleles, genotypes, and an associated genetically-inferred metabolizer phenotype (gMP) for each individual based on the recommendations of Gaedigk, et al. ${ }^{53}$ However, this approach fails to utilize the entirety of generated sequence data (i.e., targeted genotyping of specific SNVs within CYP2D6 at the exclusion of all other SNVs within the gene) so subsequent analysis of the .vcf file was performed using supervised machine learning techniques and the entire collection of genotypes from the CYP2D6 full-gene region.

Supervised machine learning makes predictions of an a priori response variable given highly dimensional input data (e.g., genotypes). ${ }^{54}$ Supervised classification was used in two ways: 1 ) to predict MP in a sample of Finns in a post-mortem setting given full-gene CYP2D6 genotype data and 2) to predict MP of the same cohort using a subset of selected loci that would provide comparable prediction accuracy as the whole set of SNVs. Four classification approaches were used with and without attribute/feature selection depending on the variable being predicted (described below) which were 1) regularized multinomial logistic regression (RMLR), 2) 1-nearest neighbor (1NN), 3) random forests (RF), and 4) linear regression (LR). Briefly, RMLR predicts a non-binary categorical variable (e.g., MP) using logistic regression that has been regularized to improve generalization (i.e., improve classifier performance when applied to new, unseen data). ${ }^{55-}$ ${ }^{58}$ The 1NN classifier assigns a categorical variable (e.g., MP or T:M1) of an unknown by finding its closest neighbor among a set of training points or data. ${ }^{56,57,59,60} \mathrm{RF}$ classifiers predict an outcome variable (e.g., MP or T:M1) by constructing a series of decision trees using input features. LR models use a combination of explanatory variables (e.g., SNV loci) to predict a numerical outcome variable (e.g., T:M1). Note that while RMLR and LR were used exclusively for
categorical and numerical variable prediction, respectively, the RF and 1NN classifiers can be used for categorical or numerical variable prediction, both of which were used in this study. Using the full set of genotypes, classification was performed in WEKA as follows: Logistic classifier attributes set to weka.classifiers.functions.Logistic -R 1.0E-8 -M -1 -
 \"weka.core.EuclideanDistance -R first-last\"" (1NN), RandomForest classifier attributes set to weka.classifiers.trees.RandomForest -P 100 -I 100 -num-slots $1-\mathrm{K} 0-\mathrm{M} 1.0-\mathrm{V} 0.001-\mathrm{S} 1$ (RF), and the LinearRegression classifier attributes set to weka.classifiers.functions.LinearRegression $-S \quad 0 \quad-R$ 1.0E-8 -num-decimal-places 4 (LR).

Cross validation was used to evaluate classifier accuracy using $\mathrm{n}-1$ cross validation where n is the number of instances (e.g., samples) for which variables (e.g., genotypes) were observed. In doing so, the size of the training set is maximized while minimizing the effects of over-fitting the data upon which the classifier is trained. ${ }^{56,57} \mathrm{~A}$ second test set also is produced which includes a single instance of all variables with which the model is tested. By performing n-fold cross validation, the model is tested once for each instance within a dataset (i.e., all instances in $n$ are used to test the model designed with $\mathrm{n}-1$ instances). Unless otherwise noted, 43 -fold cross validation was used for the work described herein.

Feature selection identifies a subset of variables/attributes/features which provide comparable predictive power to the entire set of variables. Consequently, feature selection reduces noise, eliminates features that provide minimal meaning for classifier performance, and minimizes the
effects of over-fitting. ${ }^{61,62}$ Feature selection was performed using the Select Attributes function of WEKA, the CfsSubsetEval attribute evaluator with its default settings weka.attributeSelection.CfsSubsetEval -P 1 -E 1 and default search method settings weka.attributeSelection.GreedyStepwise -T $1.7976931348623157 \mathrm{E} 308-\mathrm{N}-1$-num-slots 1.

## Results

## Sample Demography, Toxicology, and Quality

The average age of the 208 deceased individuals used in this study was 60.0 years $\pm 18.3(\mathrm{n}=$ 81) and 52.2 years $\pm 17.9(n=127)$ for females and males, respectively. All subjects expired in Finland and were assumed to be of Finnish ancestry. All individuals were assigned an alphanumeric International Classification of Diseases, Tenth Revision (ICD-10) cause of death (CoD) code at the time of medico-legal autopsy (see International Statistical Classification of Diseases and Related Health Problems 10th Revision [ICD-10]-WHO Version for 2016. http://apps.who.int/classifications/icd10/browse/2016/en\#/I; accessed 21APR2017) (Figure S1).

The average measured concentrations of tramadol and M1 and T:M1 ratio were $4.04 \mathrm{mg} / \mathrm{l} \pm$ $5.94,0.447 \pm 0.769 \mathrm{mg} / \mathrm{l}$, and $11.6 \pm 18.3$, respectively (Figure 1 ). Differences in the concentrations of tramadol and M1 or T:M1 between pairwise combinations of MoD groups or between males and females within and between MoD groups were tested using one-way analysis of variance (ANOVA) and Tukey's Honest Significant Difference test. Significant differences were observed between the concentration of tramadol in suicide and trauma ( $\mathrm{p}=1.00 \times 10^{-7}$ ) and suicide and disease $\left(p=7.65 \times 10^{-5}\right)$ MoDs and the T:M1 ratios for suicide and disease $(p=6.20$ x $10^{-4}$ ) MoDs.

Parent compound to metabolite ratios were used to infer the natural clustering of individuals in the cohort. These clusters were associated with a corresponding toxicologically-inferred metabolizer phenotype (t-MP). ${ }^{63,64}$ Here, T:M1 ratios were used for model-based clustering of each subject into a t-MP category using mclust (Figure 1). ${ }^{37,38}$ Assuming unequal variance, the sample set was divided into five components consistent with $\mathrm{PM}(5 ;$ orange; $\mathrm{T}: \mathrm{M} 1 \geq 50 ; \mathrm{N}=5$ ), $\mathrm{IM}(4 ;$ purple; $50>\mathrm{T}: \mathrm{M} 1 \geq 20 ; \mathrm{N}=20)$, NM-S (3; green; $20>\mathrm{T}: \mathrm{M} 1 \geq 8 ; \mathrm{N}=67$ ), NM-F (2; red; $8>\mathrm{T}: \mathrm{M} 1 \geq 3 ; \mathrm{N}=91)$, and $\mathrm{UM}(1 ;$ blue; $3>\mathrm{T}: \mathrm{M} 1 \geq 1 ; \mathrm{N}=25)$ phenotype resolution reported in Gaedigk, et al. ${ }^{53}$ It should be noted that the mclust package selected five as the most probable number of components due to it having the least negative Bayesian information criterion (BIC). As expected, there was a spike in classification inaccuracy where two classes meet due to ambiguity of threshold assignment between them.

Quantifiler ${ }^{\mathrm{TM}}$ Trio (Quant Trio) results were used to determine the presence of degradation and/or inhibition in the autopsy samples used for this study. The average DI was $1.47 \pm 0.631$ and ranged from 0.796 (sample collected in 2012) to 7.76 (sample collected in 2003) (Figure 1). Only four samples triggered the IPC $\mathrm{C}_{\mathrm{t}}$ flag and had DI values $>1$ indicating degradation and/or inhibition. These four samples had average DI and IPC C $C_{t}$ values of $1.26 \pm 0.220$ and $31.3 \pm 1.19$, respectively. While DI tends to be lower in newer samples, this cohort did not show a significant relationship between sample age and DI or quantity of DNA obtained from the storage medium.


Figure 1. Summaries of sample information. A) Concentration ( $\mathrm{mg} / \mathrm{l}$ ) of tramadol, Odesmethyltramadol and ratio of tramadol:O-desmethyltramadol in 208 deceased, tramadolexposed Finns stratified by sex and autopsy-determined manner of death. Note the $\log _{10}$ scale of the y-axis. B) Scatterplots of the degradation index (DI), mean cycle threshold for the internal PCR control (IPC Ct), and sample quantity (ShortAmplicon; $\mathrm{ng} / \mu \mathrm{l}$ ) by sample collection year. The relative color intensity of each data point represents the number of samples at a given $x, y$ coordinate with darker data points indicating greater sample abundance. Local polynomial regression (e.g., loess) curves (black lines) and standard error (grey shading) show general trends. C-E) Model-based clustering output of 208 deceased tramadol-exposed Finns using the tramadol/O-desmethyltramadol (T:M1) ratio. C) The most likely number of clusters assuming equal ( E ) and unequal ( V ) variance; D ) distribution of all samples (black) and their assigned clusters (different colors); E) error associated with sample assignment to each cluster. Note that the x -axis of image C is trimmed to exclude cluster 5 (orange) as to provide greater resolution of sample assignment from $0 \leq \mathrm{T}: \mathrm{M} 1 \leq 60$.

## CYP2D6 Structural Analyses

Long-range PCR was used to identify the presence of normal CYP2D6, by length, CNV, and/or CYP2D7P/CYP2D6 hybrids in each sample. Sample CYP2D6 diplotype data is presented in Table S1. Indeed, the DI and IPC $\mathrm{C}_{\mathrm{t}}$ values did not indicate overall degradation or inhibition, respectively, of the samples in this study; however, the relative amplification success of 7 kb
fragments was quite low (i.e., the total number of amplification failures was 169/208). This lower success rate has been observed ${ }^{17}$ and highlights the need for methods which rely on smaller size targets. It also should be noted that testing for sample degradation using a long (>200 bp) and short amplicon ( $75-80 \mathrm{bp}$ ) ratio, as is done with Quant Trio, may not be a good indicator of amplification success for much longer amplicons. Rahikainen, et al. ${ }^{17}$ noted that a $\mathrm{DI} \geq 1$ was indicative of poor CYP2D6 amplification. Here, poor amplification is confirmed on a larger sample set and a slight, though not significant, negative linear relationship between the Quant Trio DI value and the quantity of amplified CYP2D6 ( $\mathrm{p}=0.0693$; Pearson's $\mathrm{r}=-0.259$ ) is observed. To expand upon the Rahikainen, et al. findings, it may be reasonable to consider that as a sample DI approaches 1, CYP2D6 amplification is likely and as the sample DI exceeds 1, CYP2D6 amplification success will be lower.

The samples in which CYP2D6 amplified represented twenty ICD-10 CoDs with no significant relationship between CoD and T:M1 (ANOVA; $\mathrm{p}=0.999$ ), suggesting that the high observation of ICD-10 T36 (Poisoning by, adverse effect of, and under-dosing of systemic antibiotics) had no impact on T:M1. These 44 successfully amplified CYP2D6 products were subjected to MPS and the resultant data to machine learning to identify possible maximally informative target SNVs for CYP2D6 genetic interrogation compared with full-gene capabilities (see Metabolizer Phenotype Classification and Feature Selection).

## Sequencing Performance

Three MPS runs were performed to generate CYP2D6 full-gene sequence data with average cluster density and clusters passing filter of $952 \mathrm{k} / \mathrm{mm}^{2} \pm 496$ and $88.2 \% \pm 6.20$, respectively. After application of a 20X read depth threshold, the average sample read depth was $452 \mathrm{X} \pm 505$ (range 25.2 X to $2,925 \mathrm{X}$ ).

## CYP2D6 Single Nucleotide Variants

Raw CYP2D6 SNV .vcf files were analyzed with VCFtools to generate general population genetic summary statistics based on a locus read depth threshold of 20X. A total of 1,875 SNVs were detected with an average read depth of $361 \mathrm{X} \pm 211$ (range 21X to 2,020X). All detected sites are listed in Table S1. The average alternate allele frequency for the 571 observed heterozygous sites was $0.136 \pm 0.213$. After Bonferroni correction ( $\mathrm{p}_{\mathrm{adj}}=2.69 \times 10^{-5}$ ), there were no significant deviations from expectations of Hardy-Weinberg Equilibrium in this deceased Finnish cohort. After correction for multiple testing ( $\mathrm{p}_{\text {adj }}=2.67 \times 10^{-5}$ ), no SNVs exhibited significant association on T:M1 (data not shown).

Heritabilities $\left(h^{2}\right)$ of T:M1 and t-MP were evaluated using the full set of 1,875 SNVs using the --reml command in PLINK. Given the wide-spread application of CYP2D6 SNV and diplotype information for MP prediction, the phenotypic variance in this cohort was minimally explained and not significant $\left(\mathrm{h}^{2}{ }_{\mathrm{t}-\mathrm{MP}}: 0.0929, \mathrm{p}=0.458 ; \mathrm{h}^{2}{ }_{\mathrm{T}: \mathrm{M} 1}: 3.00 \times 10^{-6}, \mathrm{p}=0.500\right)$ with the observed variants (Table 2). Indeed, this finding on phenotypic variance using full-gene information may be indicative that the sample size is not sufficient for detecting the true heritability of phenotype and/or full-gene data may not contribute substantially to maximize explainable phenotypic variance. Hence, a subset of loci within the gene likely contribute more so to phenotype relative to all others.

Table 2. Heritability ( $h^{2}$ ) summary for the variance of rate of tramadol O-demethylation (T:M1) and the resulting toxicologically-inferred metabolizer phenotype (t-MP) in 44 samples.

| Phenotype | $\mathbf{h}^{\mathbf{2}}$ | Standard error $\left(\mathbf{h}^{\mathbf{2}}\right)$ | $\mathbf{p}$-value |
| :---: | :---: | :---: | :---: |
| T:M1 | $3 \times 10^{-6}$ | 0.787 | 0.500 |
| t-MP | 0.0929 | 0.887 | 0.458 |

## Polypharmacy

Sample polypharmacy was a potential confounding variable that may have influenced the observed concentrations of tramadol and M1, especially for co-administered CYP2D6 substrates that may compete for enzyme active sites. The drug cocktails in the 44 samples used herein were assessed using the database Transformer. ${ }^{65}$ All samples used in this study had at least one additional CYP2D6 substrate detected in their toxicology screens with no detectable patterns of commonly co-administered additional drugs or drug classes. Additionally, there were no significant correlations detected between tramadol, M1, or M1 measurements and the concentration or presence/absence of specific additional compounds. For these reasons, samples were subjected to machine learning as a single cohort of tramadol-exposed Finns, and polypharmacy was not considered a significant confounding variable for this sample cohort.

## Metabolizer Phenotype Classification and Feature Selection

The MP category and numerical T:M1 measurement (see Materials and Methods Alignment, Variant Analysis, and Machine Learning and Results Sample Demography, Toxicology, and Quality) assigned to each individual were used as the output variable for machine learning in WEKA in two phases: 1) classification with phased CYP2D6 data using the hg 19/GRCh37 reference genome, and 2) classification with unphased CYP2D6 genotype data. Both iterations were performed with and without feature selection using 1NN, LR/RMLR (depending on predicted outcome variable), and RF classifiers.

The 44 successfully amplified and sequenced CYP2D6 samples represented four t-MPs based on T:M1. In the absence of phased genotype data for CYP2D6 and assuming four t -MPs, the evaluated models modestly predicted t-MP, regardless of the supervised machine learning
algorithm (Figure 2). The average classification accuracy using all SNVs was $22.0 \% \pm 3.47$ for all three prediction algorithms used. Computational phase with the hg19/GRCh37 reference genome was performed in IMPUTE2. The overall concordance between phased and input genotypes was $95.4 \%$, indicating reliable performance of the phasing algorithm. When phase was incorporated, the mean prediction accuracy increased slightly to $25.0 \% \pm 0$; however, the increase was not significant. Feature selection increased the mean classification accuracy depending on the stringency applied during feature inclusion. Inclusion of only those features used in greater than $12 \%, 50 \%$, and $75 \%$ of cross validation folds significantly increased classification accuracies to $42.4 \% \pm 3.47,46.2 \% \pm 3.47$, and $48.5 \% \pm 4.73$, respectively $(p=0.0237,0.00881$, and 0.0351 , respectively); however, individual classifiers had relatively low prediction performance as the feature selection stringency increased. The maximum mean classification accuracy observed in this study was $52.3 \%$ after using phased genotype data and the RMLR classifier. When considering individual t-MP categories independently, t-NM-F individuals were classified well regardless of the algorithm used (mean $70.0 \% \pm 4.10 ; 2.94$-fold greater accuracy than by random chance). However, classification accuracy was low for the other three t-MPs observed in this cohort. In fact, the t-UM and t-NM-S individuals were consistently misclassified. These inaccuracies overwhelmingly represented scenarios where one t-MP was misclassified as the adjacent t-MP.
 observation is likely a consequence of binning the continuous $\mathrm{T}: \mathrm{M} 1$ variable into discrete categories or classes commonly used to represent CYP2D6 function (Figure 1E). However, using phased data, the $\mathrm{t}-\mathrm{UMs}, \mathrm{t}-\mathrm{NM}-\mathrm{Ss}$, and $\mathrm{t}-\mathrm{IMs}$ were classified with accuracies 1.35 - (32.3\%), 1.53$(36.4 \%)$, and 1.40 -fold ( $33.3 \%$ ) better than random chance alone, respectively.


Figure 2. Summary of machine learning classification accuracies for four metabolizer phenotype (MP) clusters ( $\mathrm{t}-\mathrm{UM}=$ ultra-rapid; $\mathrm{t}-\mathrm{NM}-\mathrm{F}=$ normal/extensive [fast]; $\mathrm{t}-\mathrm{NM}=$ normal/extensive ([fast] and [slow] inclusive); t-NM-S = normal/extensive [slow]; and t-IM = intermediate) using phased and unphased CYP2D6 data aligned to the hg19/GRCh37 reference genome for varying feature selection stringencies (features used in $0 \%, 12 \%, 25 \%, 50 \%$, and $75 \%$ of cross-validation folds) compared to the accuracy of the model using all genotype data from CYP2D6. Three machine learning algorithms are depicted: 1-nearest neighbor ( 1 NN ), random forest (RF), and regularized multinomial logistic regression (RMLR); dashed lines represent the average predictive accuracy due to random chance ( $23.8 \% ; 10 \%$-trimmed mean). Note that the number of clusters relative to Figure 1C are also indicated (e.g., hg19_Phased_5 and hg19_Phased_3 indicate the use of five and three clusters, respectively, for prediction).

To evaluate the influence of binning error on the predictions observed in Figure 2, additional bins were created at the boundaries of each MP. In doing so, a sample may be classified as one of the four observed MP clusters (t-UM, t-NM-F, t-NM-S, or t-IM) or as a boundary-type, indicating that ambiguity exists in classifying that individual into one of the four main categories (Figure 1E), but the sample may belong to one of two categories separated by the boundary ( $\mathrm{t}-\mathrm{UM} / \mathrm{t}-\mathrm{NM}-\mathrm{F}, \mathrm{t}-$

NM-F/t-NM-S, or t-NM-S/t-IM). The RLMR, 1 NN , and RF classifiers were used in the same manner as above with five levels of feature inclusion stringency. Using phased and unphased genotype data, the addition of extra bins decreased classification accuracy such that the maximum achievable accuracy was $25 \%$ with the RMLR classifier using the phased genotypes feature selected to include SNVs involved in > 50 folds (data not shown). Alternatively, capturing only clinically relevant-differences in MP by allowing for classification of a single sample into t-UM, t -NM (inclusive of fast $[\mathrm{F}]$ and slow $[\mathrm{S}]$ while not penalizing the inaccuracy of deciding between the two), or $\mathrm{t}-\mathrm{IM}^{53}$ (Figures 1C and 1E) increased mean classification accuracies of all three MPs to $33.7 \% \pm 8.89,86.4 \% \pm 5.65$, and $50 \% \pm 0$ for $\mathrm{t}-\mathrm{UM}, \mathrm{t}-\mathrm{NM}$ (inclusive of fast and slow), and t IM, respectively (Figure 2). As seen with finer MP resolution above, using phased genotype data significantly increased mean classification accuracies for inclusion of features used in $>25 \%, 50 \%$, and $75 \%$ of cross-validation folds $\left(\mathrm{p}=0.0136,4.82 \times 10^{-4}\right.$, and $9.74 \times 10^{-3}$, respectively). Interestingly, using unphased genotypes without feature selection and the RF classifier predicted NMs with a maximum accuracy of $96.3 \%$. This level of accuracy was not significantly affected with the introduction of phased genotypes and increased feature inclusion stringency.

The LR, 1NN, and RF classifiers were used to predict the T:M1 continuous variable. Using all unphased SNVs, predictions with all three algorithms were modestly inaccurate with an average difference in actual and predicted $\mathrm{T}: \mathrm{M} 1(\Delta \mathrm{~T}: \mathrm{M} 1)$ of $-0.117 \pm 13.8$, indicating slight underestimation of T:M1 (Figure 3). There were no significant differences between the actual and predicted values of T:M1 due to choice of machine learning algorithm given all unphased SNVs. Incorporation of phased genotype information significantly exacerbated the underestimation of T:M1 by decreasing the mean $\Delta \mathrm{T}: \mathrm{M} 1$ to $-6.71 \pm 34.8(\mathrm{p}=0.0186)$. The 1 NN and RF classifiers did not exhibit differences between actual and predicted T:M1; however, the LR classifier
produced significantly lower predictions of T:M1 relative to the actual value $(\mathrm{p}=0.0228)$ if given phased data to the CYP2D6 locus. Feature selection was performed by assessing the same five thresholds for feature inclusion as the categorical variable predictions described above (>0\%,> $12 \%,>25 \%,>50 \%$, and $>75 \%$ ). Unlike the increased accuracies observed in Figure 2 for feature selected t-MP predictions, there were no significant changes in $\Delta \mathrm{T}: \mathrm{M} 1$ given attribute selected loci, indicating prediction accuracies no better than random chance for any of the five feature inclusion thresholds.


Figure 3. Summary of machine learning predicted tramadol:O-desmethyltramadol (T:M1) ratios using phased and unphased CYP2D6 data aligned to the hg19/GRCh37 reference genome for varying feature selection stringencies (features used in $0 \%, 12 \%, 25 \%, 50 \%$, and $75 \%$ of crossvalidation folds) compared to the observed toxicologically determined T:M1. The shading of data points is scaled to represent the relative abundance of data points along the $x=y$ diagonal; dashed lines represent the average predictive accuracy due to random chance ( $6.67 ; 10 \%$-trimmed mean).

To evaluate how few SNV loci could be used to predict t-MP and T:M1, five different thresholds were applied to the data during feature selection; these thresholds included features involved in $>0 \%,>12 \%,>25 \%,>50 \%$, and $>75 \%$ of the folds performed during crossvalidation. By incorporating features used in $>75 \%$ of the cross validation folds, the mean accuracy in predicting t-MP was significantly greater than that of the entire set of SNVs in the CYP2D6 region ( $\mathrm{p}<0.0351$ ). This finding suggests that instead of using the entire set of 1,875

SNVs detected in the CYP2D6 gene region to predict MP of this study cohort, it may be reasonable to type only seven loci (i.e., a 268 -fold reduction in the number of loci required to make a prediction), while also considering biological sex (Table 3). The loci are NC_000022.10:c.*428G>A, NC_000022.10:c.*264G>A, NC_000022.10:c.352+308G>A, NC_000022.10:c.181-347A>G, NC_000022.10:c.-43insG, NC_000022.10:c.-560A>G, and NC_000022.10:c.-1431C>T (Table 3). For predicting T:M1, there were no significant differences between $\Delta \mathrm{T}$ :M1 for phased versus unphased data, RF versus LR versus 1 NN classifiers, or classification accuracies using various feature inclusion criteria. For T:M1, it may be reasonable to reduce the number of loci by 150 -fold. Predicting the T:M1 phenotype can be achieved using presence/absence information for fragments A and H and genotype information for the following 12 loci: NC_000022.10:c.*378T>A, NC_000022.10:c.*264G>A, NC_000022.10:c.1441T>C, NC_000022.10:c.1316-1G>A, NC_000022.10:c.1315+32T>C, NC_000022.10:c.1117G>A, NC_000022.10:c.1094G>A, NC_000022.10:c.837-18G>C, NC_000022.10:c.755A>G, NC_000022.10:c. $666+118 \mathrm{~A}>\mathrm{C}$, NC_000022.10:c.-194C>T, and NC_000022.10:c.-1243A>G (Table 3). Interestingly, the common gene duplication detected with fragment $B$ was not meaningful for predicting T:M1 in this cohort.

Table 3. Selected features used in more than $75 \%$ of the cross validation folds to predict toxicologically inferred metabolizer phenotype (t-MP) and/or tramadol:O-desmethyltramadol ratio (T:M1). Relevant additional information is provided for each locus, including conferred amino acid change, relative position on two other relevant reference sequences (hg38/GRCh38 and M33388), the Finnish minor allele frequency (MAF) observed in this sampling of deceased Finns, and the global MAF.

| Locus rs Number | DNA <br> Sequence Change* | Hg19/GRCh3 <br> 7 Coordinate | hg19/GRCh3 <br> 7 Reference Allele | Amino <br> Acid <br> Chang <br> e | Hg38/GRCh3 <br> 8 Coordinate | M33388 <br> Coordinat <br> e | MAF | Globa 1 MAF | Used to predic t |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| - | c. $* 428 \mathrm{G}>\mathrm{A}$ | 42522148 | G | - | 42126146 | 4645 | 0.0147 | 0.00 | t-MP |
| - | c.*378T>A | 42522198 | T | - | 42126196 | 4595 | 0.0156 | 0.00 | T:M1 |
| $\begin{gathered} \mathrm{rs} 116390392 \\ / \\ \mathrm{rs} 12169962^{\dagger} \\ \hline \end{gathered}$ | c. $* 264 \mathrm{G}>\mathrm{A}$ | 42522312 | G | - | 42126310 | 4481 | 0.545 | 0.239 | $\begin{aligned} & \hline \text { t-MP } \\ & \text { and } \\ & \text { T:M1 } \\ & \hline \end{aligned}$ |
| rs1135838 | c. $1441 \mathrm{~T}>\mathrm{C}$ | 42522629 | T | F481V | 42126627 | 4164 | 0.0147 | 0.00 | T:M1 |
| - | c. $1316-1 \mathrm{G}>\mathrm{A}$ | 42522755 | G | Intron | 42126753 | 4038 | 0.0152 | 0.00 | T:M1 |
| - | c. $1315+32 \mathrm{~T}>\mathrm{C}$ | 42522821 | T | Intron | 42126819 | 3972 | 0.0152 | 0.00 | T:M1 |
| rs150552908 | c. $1117 \mathrm{G}>\mathrm{A}$ | 42523505 | G | G373G | 42127503 | 3288 | 0.0156 | 0.00 | T:M1 |
| rs1058172 | c.1094G>A | 42523528 | G | R365H | 42127526 | 3265 | 0.0156 | 0.00 | T:M1 |
| - | c. $837-18 \mathrm{G}>\mathrm{C}$ | 42524003 | G | Intron | 42128001 | 2790 | 0.0152 | 0.00 | T:M1 |
| - | c. $755 \mathrm{~A}>\mathrm{G}$ | 42524264 | A | D252V | 42128262 | 2529 | 0.0152 | 0.00 | T:M1 |
| - | $\begin{gathered} \text { c. } 666+118 \mathrm{~A}> \\ \mathrm{C} \end{gathered}$ | 42524669 | A | Intron | 42128667 | 2124 | 0.156 | 0.00 | T:M1 |
| - | $\begin{gathered} \hline \mathrm{c} .352+308 \mathrm{G}> \\ \mathrm{A} \end{gathered}$ | 42525431 | G | Intron | 42129429 | 1363 | 0.0151 | 0.00 | t-MP |
| - | c. $181-347 \mathrm{~A}>\mathrm{G}$ | 42526258 | A | Intron | 42130256 | 536 | $\begin{gathered} 0.0312 \\ 5 \end{gathered}$ | 0.00 | t-MP |
| rs75085559 ${ }^{\dagger}$ | c. -43 insG | 42526836 | - | - | 42130834 | -43 | 0.0114 | $\begin{gathered} 0.043 \\ 5 \end{gathered}$ | t-MP |
| - | c.-194C>T | 42526987 | C | - | 42130985 | -194 | 0.0469 | 0.00 | T:M1 |
| - | c. $-560 \mathrm{~A}>\mathrm{G}$ | 42527353 | A | - | 42131351 | -560 | 0.0156 | 0.00 | t-MP |
| - | c. $-1243 \mathrm{~A}>\mathrm{G}$ | 42528036 | A | - | 42132029 | -1238 | 0.0667 | 0.00 | T:M1 |
| rs28588594 ${ }^{\dagger}$ | c. $-1431 \mathrm{C}>\mathrm{T}$ | 42528224 | C | - | 42132217 | -1426 | 0.148 | 0.240 | t-MP |
| Fragment H (Presence or Absence) | NA | NA | NA | NA | NA | NA | NA | NA | T:M1 |

*Nucleotide numbering is based on the negative DNA strand of reference sequence NC_000022.10 (hg19/GRCh37).
$\dagger$ Locus is recognized in CYP2D6 haplotype definitions reported by PharmVar.

Student's t-tests were used to compare the mean T:M1 between genotypes at each locus in
Table 3 in a pairwise manner for only those loci with more than one observation of each genotype in the sample set (i.e., NC_000022.10:c.*264G>A, NC_000022.10:c.-1243A>G, and NC_000022.10:c.-1431C>T; Figure S2). There were no significant differences between T:M1 for pairwise combinations of genotypes at NC_000022.10:c.*264G>A or NC_000022.10:c.$1431 \mathrm{C}>\mathrm{T}$; however, there was a significantly lower mean T:M1 for those individuals carrying the G allele at NC_000022.10:c.-1243A>G(N=3;p=0.00137; Figure S2). This locus is not currently
reported by PharmVar as a defining locus for CYP2D6 haplotypes and while these data suggest the downstream variant impacts function, a larger sample size may be needed to validate the impact of the locus on CYP2D6 activity with respect to tramadol O-demethylation. It should be noted that additional, potentially damaging loci were detected in this cohort: NC_000022.10:c.1094G>A (SIFT: Damaging [0.00]; PROVEAN: Deleterious [-3.46]) and NC_000022.10:c.755A>G (SIFT: Tolerated [0.0647]; PROVEAN: [-4.81]) Only four loci identified for t-MP and T:M1 prediction are currently recognized by PharmVar as part of CYP2D6 haplotypes: NC_000022.10:c.*264G>A $(\mathrm{M} 33388: 4481 \mathrm{G}>\mathrm{A} ; \quad$ CYP2D6*2, *11, *31, *65, *69, *84, and *102-*105), NC_000022.10:c.1117G>A (M33388:G>A; CYP2D6*6), NC_000022.10:c.-43insG (M33388; undetermined but detected), and NC_000022.10:c.-1431C>T (M33388C>T; CYP2D6*4, *10, $* 21, * 36, * 47, * 49, * 52, * 56, * 58, * 64, * 68, * 69, * 72$, and $* 99-* 101)$. Note that while causal loci conferring abnormal CYP2D6 activity (i.e., conferring g-PM, g-IM, or g-UM) are not represented in Table 3, there was significant enrichment of the NC_000022.10:c.*264A allele in the autopsied Finns relative to the global minor allele frequency from the 1000 Genomes Project ( $\mathrm{p}=3.76 \times 10^{-}$ $\left.{ }^{8}\right)$. The inverse observation is true for the NC_000022.10:c.-1431T allele $(p=0.0331)$.

## CYP2D6 Haplotype

Phased genotype variant call files were used as input for the CYP2D6 VCF Translator. The output of the translator was used to infer CYP2D6 * allele assignments for each individual consistent with PharmVar recognized haplotypes (www.PharmVar.com; i.e., only those loci recognized by PharmVar were analyzed). Due to the relatively small sample size of this study, CYP2D6 * allele frequencies are not reported but full-gene haplotypes are provided in Supplemental Table 2. Individuals exhibiting hybrid- and/or duplication-positive amplicons by
long-range PCR were excluded from estimates of haplotype diversity as similarity of the regions of CYP2D6 and CYP2D7 may contribute to producing a hybrid locus or private mutations unique to a single CYP2D6 duplicate. In the 33 samples positive for Fragment A only (i.e., these individuals lack CYP2D7P/CYP2D6 hybrids and CYP2D6 duplications), there were 51/66 unique haplotypes. The CYP2D6 full-gene haplotype diversity was 0.972 .

Distributions of g-MP and t-MP were compared using a chi-squared goodness of fit test. There were significant differences between the two MP distributions ( $\mathrm{p}=3.31 \times 10^{-15}$ ) indicating genotype-phenotype discordance. The magnitude of this difference; however, is similar with previous reports of various global populations, ${ }^{13,66-68}$ but to our knowledge, this is the first report in Finns. Most of this discordance was due to differences in classifying individuals into the fast (NM-F) and slow (NM-S) designations of the NM phenotype class. Using genetic data (g-MP), 28/44 and 8/44 samples were considered NM-F and NM-S, respectively, while using toxicology data (t-MP), these categories contained 14/44 and 13/44 samples, respectively.

## Discussion

The CYP2D6 locus, and indeed many pharmaco- and immunogenes, can be challenging to amplify by long PCR, and thus sequence and interpret using current restriction digestion and subsequent computational methods. This study successfully amplified the full CYP2D6 region in a subset of a deceased Finnish cohort. Though not a significant confounding variable, overall poor amplification success was possibly due to the degree of degradation observed in samples stored on FTA paper, generally confirming the observations of Rahikainen, et al. ${ }^{17}$ These studies suggest that large targets are quite difficult to amplify from FTA-deposited substrates, an important observation for medico-legal autopsy, bio-banking, and clinical diagnostics.

The goal of this study was to identify a minimal set of maximally informative CYP2D6 SNVs and evaluate the necessity of phased genotype information for predicting phenotype. Full-gene haplotype information was generated using short-read DNA sequencing and subsequent computational phasing. To our knowledge, there are few reports of full-gene information for the CYP2D6 locus ${ }^{69,70}$ but these data are useful for expanding the pharmacogenomics and personalized medicine community's knowledge of how full-gene interrogation of various genes may impact the understanding of the genotype-phenotype relationship. ${ }^{71}$ Generally, phased genotyping information from CYP2D6 predicted MP with substantially greater accuracy than raw genotypes, especially for non-NM individuals. This finding is unsurprising but emphasizes a limitation of interrogating pharmaco- and immunogenes for predicting a number of metabolically relevant phenotypes.

Using current approaches by identifying key CYP2D6 star-allele defining variants has proven inaccurate in some populations. ${ }^{13,66-68}$ While somewhat inaccurate, there is a tradeoff involved with obtaining more, possibly uninformative full-gene genotype data and maximizing assay real estate, specifically in terms of short-read DNA sequencing library preparation panel development. For example, obtaining full-gene CYP2D6 information for some populations may provide slightly increased phenotype prediction accuracy, but limits sequencing throughput and for archived samples, full-gene amplification and subsequent typing success may be quite low. Conversely, a core set of seven loci, identified and evaluated herein using supervised machine learning techniques, may predict MP with increased accuracy relative to random chance and comparable with that of full-gene information, thereby increasing the typing success of many archived samples. These findings potentially enable creation of SNV-targeted MPS library preparation panels
specific to pharmacogenetics population studies and promote easy and cost effective clinical applications of CYP2D6 data.

Subsequent evaluations of the capability to predict the actual ratio of parent compound to metabolite (T:M1) also were performed with modest success depending on the method employed. Interestingly, the LR, RF, and 1 NN machine learning algorithms could not accurately predict the $\mathrm{T}: \mathrm{M} 1$ ratio any better than random chance, and required knowledge of whether an individual contains a hybrid allele (detected by fragment H). However, predicting the exact ratio of parent drug to primary metabolite may not be the most clinically relevant application of CYP2D6 genotype information as individuals are currently binned into general classes of MP describing a range of ratios (e.g., T:M1). Consequently, while the actual and predicted values of T:M1 were quite different and indeed biologically relevant, the clinical significance of poor T:M1 prediction may be uninformative.

Seven and 12 loci (with one overlapping SNV) out of 1,875 SNVs (a 103-fold reduction in loci) were selected to predict T:M1 and t-MP, respectively, in this cohort of Finnish individuals. Interestingly, the nonpathogenic, downstream CYP2D6 variant NC_000022.10:c.*264G>A (also known as rs116390392, rs12169962, M33388:4481G>A) was a key feature for predicting both tMP and T:M1 in Finns at the highest level of feature inclusion stringency (i.e., the locus was used in $>75 \%$ of cross-validation folds). In fact, this SNV also was one of only four PharmVar loci identified after application of the maximum feature inclusion stringency threshold (including NC_000022.10:c.1117G>A, NC_000022.10:c.-43insG and NC_000022.10:c.-1431C>T). These four SNVs are located in the $5^{\prime}$ and $3^{\prime}$ untranslated regions (UTRs) or are not known to be causal; however, according to PharmVar, the NC_000022.10:c.1117G>A locus has only been reported in an allele conferring an inactive CYP2D6 enzyme (CYP2D6*6). The CYP2D6*6:1707delT variant
is considered the defining variant of this haplotype because it produces a deleterious frameshift mutation, making the presence of NC_000022.10:c.1117G>A meaningless. However, NC_000022.10:c.1117G>A may additionally contribute to enzyme inactivity in other haplotypes as suggested by the deceased Finns. Though only three samples had the alternate allele at NC_000022.10:c.-1243A>G, which appears to be a putatively identified novel variant in the 3 ' UTR. In this cohort of deceased Finns, the presence of the $G$ allele was associated with a faster rate of tramadol O-demethylation, as indicated by a decrease in T:M1. There were general trends observed at the remaining 17 loci, but in the absence of more than one observation of the alternate allele/genotype, conclusions regarding their functional impact are not presented. While these loci offered predictive power in a cohort of deceased Finns, the application of that power in non-Finnish European, other global populations, and non-tramadol opioid users must be evaluated.

The relative absence of PharmVar loci after application of the most stringent feature selection threshold is quite interesting; however, the majority of successful CYP2D6 amplifications were indicated as normal metabolizers, which could explain the relative lack of clinically relevant SNV enrichment. Alternatively, there are a number of relatively infrequent SNVs which confer variable CYP2D6 activity. The lack of these loci as most meaningful for phenotype classification my supervised machine learning may be an artifact of global rarity and unsteady presence/absence in the extreme CYP2D6-inferred MPs. In other words, the clinical relevance of the SNVs detected here should not influence the relative usefulness of each locus for predicting phenotype by these machine learning algorithms.

The samples used in this study are from medico-legal autopsies which raises two key limitations: 1) each sample had detectable concentrations of other compounds in their blood, and 2) the $\mathrm{T}: \mathrm{M} 1$ ratio may not accurately reflect the rate of tramadol O-demethylation in clinical
patients due to post-mortem redistribution and/or time between tramadol administration and death. It is reasonable to hypothesize that polypharmacy (i.e., the administration or use of more than one medication or drug for at least one medical condition or recreation ${ }^{72}$ ) would negatively impact the predictability of the MP, especially when multiple CYP2D6 substrates are co-administered at or above the recommended dose. Polypharmacy would likely manifest as inaccurate and/or discordant MP predictions when using genetic and toxicological data. Though not a readily apparent confounding variable in this study, polypharmacy will require more systematic controls and large sample sizes to detect and accurately characterize specific interactions between combinations of two, three, four, or more compounds. ${ }^{72}$

Significant differences in t-MP and g-MP distributions were observed, indeed representing diplotype-phenotype discordance, especially for the NM-S versus NM-F MPs. The measurement of t-MP using T:M1 is a key limitation that may have contributed to this difference in distribution as there was no knowledge or control of the tramadol concentration delivered to each sample, postmortem tramadol and/or O-desmethyltramadol redistribution, or the time between tramadol dosing and O-desmethyltramadol detection. This discordance also might be influenced by limited data. It is known that drug ADME (absorption, distribution, metabolism, and excretion) and response are pathway-dependent processes; however, most clinical applications use only CYP2D6. Given the relatively low heritability described here, it is likely that a combinatorial genetic predictive model will increase classification accuracies by explaining a greater proportion of phenotypic variance and providing a more complete picture of tramadol ADME and response.

The opioid analgesic tramadol was used as a model drug to identify and evaluate a set of maximally predictive CYP2D6 loci. Predicting tramadol without full-gene CYP2D6 data is highly desirable and may provide a level of accuracy, depending on the MP in question. However, the
model may not apply to non-tramadol opiates, or other CYP2D6 substrates. Future work should evaluate the efficacy of a minimal collection of SNVs on other, non-tramadol opiates, and more broad classes of CYP2D6 substrates to identify if the subset of features identified here are equally informative of codeine to morphine conversion, for example. In doing so, a predictive model may be constructed which incorporates SNVs from multiple candidate genes to predict response to a battery of drugs and toxins.

## References

[1] DePriest AZ, Puet BL, Holt AC, Roberts A, Cone EJ. Metabolism and Disposition of Prescription Opioids: A Review. Forensic science review. 2015;27:115-45.
[2] Gong L, Stamer UM, Tzvetkov MV, Altman RB, Klein TE. PharmGKB summary: tramadol pathway. Pharmacogenet Genomics. 2014;24:374-80.
[3] Pedersen RS, Damkier P, Brosen K. Enantioselective pharmacokinetics of tramadol in CYP2D6 extensive and poor metabolizers. Eur J Clin Pharmacol. 2006;62:513-21.
[4] Fonseca S, Amorim A, Costa HA, Franco J, Porto MJ, Santos JC, Dias M. Sequencing CYP2D6 for the detection of poor-metabolizers in post-mortem blood samples with tramadol. Forensic Sci Int. 2016;265:153-9.
[5] Lassen D, Damkier P, Brosen K. The Pharmacogenetics of Tramadol. Clinical pharmacokinetics. 2015;54:825-36.
[6] Ingelman-Sundberg M. Genetic polymorphisms of cytochrome P450 2D6 (CYP2D6): clinical consequences, evolutionary aspects and functional diversity. Pharmacogenomics J. 2005;5:6-13.
[7] Ingelman-Sundberg M, Sim SC, Gomez A, Rodriguez-Antona C. Influence of cytochrome P450 polymorphisms on drug therapies: pharmacogenetic, pharmacoepigenetic and clinical aspects. Pharmacology \& therapeutics. 2007;116:496-526.
[8] Zhou SF. Polymorphism of human cytochrome P450 2D6 and its clinical significance: Part I. Clinical pharmacokinetics. 2009;48:689-723.
[9] Zhou SF. Polymorphism of human cytochrome P450 2D6 and its clinical significance: part II. Clinical pharmacokinetics. 2009;48:761-804.
[10] Zhou SF, Di YM, Chan E, Du YM, Chow VD, Xue CC, Lai X, Wang JC, Li CG, Tian M, Duan W. Clinical pharmacogenetics and potential application in personalized medicine. Current drug metabolism. 2008;9:738-84.
[11] Cheng S, Fockler C, Barnes WM, Higuchi R. Effective amplification of long targets from cloned inserts and human genomic DNA. Proc Natl Acad Sci U S A. 1994;91:5695-9.
[12] Gaedigk A, Bradford LD, Alander SW, Leeder JS. CYP2D6*36 gene arrangements within the cyp2d6 locus: association of CYP2D6*36 with poor metabolizer status. Drug metabolism and disposition: the biological fate of chemicals. 2006;34:563-9.
[13] Gaedigk A, Bradford LD, Marcucci KA, Leeder JS. Unique CYP2D6 activity distribution and genotype-phenotype discordance in black Americans. Clin Pharmacol Ther. 2002;72:76-89.
[14] Gaedigk A, Gotschall RR, Forbes NS, Simon SD, Kearns GL, Leeder JS. Optimization of cytochrome P4502D6 (CYP2D6) phenotype assignment using a genotyping algorithm based on allele frequency data. Pharmacogenetics. 1999;9:669-82.
[15] Gaedigk A, Ndjountche L, Divakaran K, Dianne Bradford L, Zineh I, Oberlander TF, Brousseau DC, McCarver DG, Johnson JA, Alander SW, Wayne Riggs K, Steven Leeder J. Cytochrome P4502D6 (CYP2D6) gene locus heterogeneity: characterization of gene duplication events. Clin Pharmacol Ther. 2007;81:242-51.
[16] Lundqvist E, Johansson I, Ingelman-Sundberg M. Genetic mechanisms for duplication and multiduplication of the human CYP2D6 gene and methods for detection of duplicated CYP2D6 genes. Gene. 1999;226:327-38.
[17] Rahikainen AL, Palo JU, de Leeuw W, Budowle B, Sajantila A. DNA quality and quantity from up to 16 years old post-mortem blood stored on FTA cards. Forensic Sci Int. 2016;261:14853.
[18] Sistonen J, Fuselli S, Levo A, Sajantila A. CYP2D6 genotyping by a multiplex primer extension reaction. Clinical chemistry. 2005;51:1291-5.
[19] Frost J, Lokken TN, Helland A, Nordrum IS, Slordal L. Post-mortem levels and tissue distribution of codeine, codeine-6-glucuronide, norcodeine, morphine and morphine glucuronides in a series of codeine-related deaths. Forensic Sci Int. 2016;262:128-37.
[20] Levo A, Koski A, Ojanpera I, Vuori E, Sajantila A. Post-mortem SNP analysis of CYP2D6 gene reveals correlation between genotype and opioid drug (tramadol) metabolite ratios in blood. Forensic Sci Int. 2003;135:9-15.
[21] Drögemoller BI, Wright GE, Niehaus DJ, Emsley R, Warnich L. Next-generation sequencing of pharmacogenes: a critical analysis focusing on schizophrenia treatment. Pharmacogenet Genomics. 2013;23:666-74.
[22] Wright GE, Carleton B, Hayden MR, Ross CJ. The global spectrum of protein-coding pharmacogenomic diversity. Pharmacogenomics J. 2016.
[23] Browning SR, Browning BL. Haplotype phasing: existing methods and new developments. Nat Rev Genet. 2011;12:703-14.
[24] Kong A, Masson G, Frigge ML, Gylfason A, Zusmanovich P, Thorleifsson G, Olason PI, Ingason A, Steinberg S, Rafnar T, Sulem P, Mouy M, Jonsson F, Thorsteinsdottir U, Gudbjartsson DF, Stefansson H, Stefansson K. Detection of sharing by descent, long-range phasing and haplotype imputation. Nature genetics. 2008;40:1068-75.
[25] Marchini J, Cutler D, Patterson N, Stephens M, Eskin E, Halperin E, Lin S, Qin ZS, Munro HM, Abecasis GR, Donnelly P. A comparison of phasing algorithms for trios and unrelated individuals. Am J Hum Genet. 2006;78:437-50.
[26] Hodges LM, Markova SM, Chinn LW, Gow JM, Kroetz DL, Klein TE, Altman RB. Very important pharmacogene summary: ABCB1 (MDR1, P-glycoprotein). Pharmacogenet Genomics. 2011;21:152-61.
[27] Sai K, Itoda M, Saito Y, Kurose K, Katori N, Kaniwa N, Komamura K, Kotake T, Morishita H, Tomoike H, Kamakura S, Kitakaze M, Tamura T, Yamamoto N, Kunitoh H, Yamada Y, Ohe Y, Shimada Y, Shirao K, Minami H, Ohtsu A, Yoshida T, Saijo N, Kamatani N, Ozawa S, Sawada J. Genetic variations and haplotype structures of the ABCB1 gene in a Japanese population: an expanded haplotype block covering the distal promoter region, and associated ethnic differences. Annals of human genetics. 2006;70:605-22.
[28] Sai K, Kaniwa N, Itoda M, Saito Y, Hasegawa R, Komamura K, Ueno K, Kamakura S, Kitakaze M, Shirao K, Minami H, Ohtsu A, Yoshida T, Saijo N, Kitamura Y, Kamatani N, Ozawa S, Sawada J. Haplotype analysis of ABCB1/MDR1 blocks in a Japanese population reveals genotype-dependent renal clearance of irinotecan. Pharmacogenetics. 2003;13:741-57.
[29] Ammar R, Paton TA, Torti D, Shlien A, Bader GD. Long read nanopore sequencing for detection of HLA and CYP2D6 variants and haplotypes. F1000Research. 2015;4:17.
[30] Goodwin S, McPherson JD, McCombie WR. Coming of age: ten years of next-generation sequencing technologies. Nat Rev Genet. 2016;17:333-51.
[31] Ip CLC, Loose M, Tyson JR, de Cesare M, Brown BL, Jain M, Leggett RM, Eccles DA, Zalunin V, Urban JM, Piazza P, Bowden RJ, Paten B, Mwaigwisya S, Batty EM, Simpson JT, Snutch TP, Birney E, Buck D, Goodwin S, Jansen HJ, O'Grady J, Olsen HE. MinION Analysis and Reference Consortium: Phase 1 data release and analysis. F1000Research. 2015;4:1075.
[32] Lindberg MR, Schmedes SE, Hewitt FC, Haas JL, Ternus KL, Kadavy DR, Budowle B. A Comparison and Integration of MiSeq and MinION Platforms for Sequencing Single Source and Mixed Mitochondrial Genomes. PloS one. 2016;11:e0167600.
[33] Kim BY, Park JH, Jo HY, Koo SK, Park MH. Optimized detection of insertions/deletions (INDELs) in whole-exome sequencing data. PloS one. 2017;12:e0182272.
[34] Kugelman JR, Wiley MR, Nagle ER, Reyes D, Pfeffer BP, Kuhn JH, Sanchez-Lockhart M, Palacios GF. Error baseline rates of five sample preparation methods used to characterize RNA virus populations. PloS one. 2017;12:e0171333.
[35] Liao P, Satten GA, Hu YJ. PhredEM: a phred-score-informed genotype-calling approach for next-generation sequencing studies. Genetic epidemiology. 2017;41:375-87.
[36] Maruki T, Lynch M. Genotype Calling from Population-Genomic Sequencing Data. G3 (Bethesda, Md). 2017;7:1393-404.
[37] Fraley C, Raferty AE. Model-based clustering, discriminant analysis, and density estimation. Journal of the American Statistical Association. 2002;97:611-31.
[38] Scrucca L, Fop M, Murphy TB, Raftery AE. mclust 5: Clustering, Classification and Density Estimation Using Gaussian Finite Mixture Models. The R journal. 2016;8:289-317.
[39] QIAamp(R) DNA Mini and Blood Mini Handbook Fifth Edition May 2016.
[40] Quantifiler ${ }^{\text {TM }}$ HP and Trio DNA Quantification Kits User Guide. Publication Number 4485354 Revision G
[41] Qubit® dsDNA BR Assay Kits. MAN0002325. MP32850. Revision A.0.
[42] Nextera XT DNA Library Prep Kit Reference Guide. Document \# 15031942 v02.
[43] MiSeq(R) System Guide September 2015 Document \# 15027617 v01 https://support.illumina.com/content/dam/illumina-support/documents/documentation/system_documentation/miseq/miseq-system-guide-1502761701.pdf.
[44] Li H. A statistical framework for SNP calling, mutation discovery, association mapping and population genetical parameter estimation from sequencing data. Bioinformatics (Oxford, England). 2011;27:2987-93.
[45] Li H, Durbin R. Fast and accurate short read alignment with Burrows-Wheeler transform. Bioinformatics (Oxford, England). 2009;25:1754-60.
[46] Li H, Handsaker B, Wysoker A, Fennell T, Ruan J, Homer N, Marth G, Abecasis G, Durbin R. The Sequence Alignment/Map format and SAMtools. Bioinformatics (Oxford, England). 2009;25:2078-9.
[47] McKenna A, Hanna M, Banks E, Sivachenko A, Cibulskis K, Kernytsky A, Garimella K, Altshuler D, Gabriel S, Daly M, DePristo MA. The Genome Analysis Toolkit: a MapReduce framework for analyzing next-generation DNA sequencing data. Genome research. 2010;20:1297303.
[48] Danecek P, Auton A, Abecasis G, Albers CA, Banks E, DePristo MA, Handsaker RE, Lunter G, Marth GT, Sherry ST, McVean G, Durbin R. The variant call format and VCFtools. Bioinformatics (Oxford, England). 2011;27:2156-8.
[49] Purcell S, Neale B, Todd-Brown K, Thomas L, Ferreira MA, Bender D, Maller J, Sklar P, de Bakker PI, Daly MJ, Sham PC. PLINK: a tool set for whole-genome association and populationbased linkage analyses. Am J Hum Genet. 2007;81:559-75.
[50] Yang J, Lee SH, Goddard ME, Visscher PM. GCTA: a tool for genome-wide complex trait analysis. Am J Hum Genet. 2011;88:76-82.
[51] Howie BN, Donnelly P, Marchini J. A flexible and accurate genotype imputation method for the next generation of genome-wide association studies. PLoS genetics. 2009;5:e1000529.
[52] Qiao W, Wang J, Pullman BS, Chen R, Yang Y, Scott SA. The CYP2D6 VCF Translator. Pharmacogenomics J. 2017;17:301-3.
[53] Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2017;19:69-76.
[54] Libbrecht MW, Noble WS. Machine learning applications in genetics and genomics. Nat Rev Genet. 2015;16:321-32.
[55] Engel J. Polytomous logistic regression. Statistica Neerlandica. 1988;42:233.
[56] Schmedes SE, Woerner AE, Budowle B. Forensic human identification using skin microbiomes. Applied and environmental microbiology. 2017.
[57] Schmedes SE, Woerner AE, Novroski NMM, Wendt FR, King JL, Stephens KM, Budowle B. Targeted sequencing of clade-specific markers from skin microbiomes for forensic human identification. Forensic science international Genetics. 2018;32:50-61.
[58] Wu MY, Zhang XF, Dai DQ, Ou-Yang L, Zhu Y, Yan H. Regularized logistic regression with network-based pairwise interaction for biomarker identification in breast cancer. BMC bioinformatics. 2016;17:108.
[59] Altman NS. An introduction to kernel and nearest-neighbor nonparametric regression. The American Statistician. 1992;46:175-85.
[60] Coomans D, Massart DL. Alternative k-nearest neighbor rules in supervised pattern recognition: Part 1. K-nearest neighbor classification using alternative voting rules. Analytica Chimica Acta.136:15-27.
[61] Bermingham ML, Pong-Wong R, Spiliopoulou A, Hayward C, Rudan I, Campbell H, Wright AF, Wilson JF, Agakov F, Navarro P, Haley CS. Application of high-dimensional feature selection: evaluation for genomic prediction in man. Scientific reports. 2015;5:10312.
[62] James G, Witten D, HAstie T, Tibshirani R. An Introduction to Statistical Learning with Applications in R: Springer; 2013.
[63] Chen R, Wang H, Shi J, Shen K, Hu P. Cytochrome P450 2D6 genotype affects the pharmacokinetics of controlled-release paroxetine in healthy Chinese subjects: comparison of traditional phenotype and activity score systems. Eur J Clin Pharmacol. 2015;71:835-41.
[64] Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS. The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther. 2008;83:234-42.
[65] Hoffmann MF, Preissner SC, Nickel J, Dunkel M, Preissner R, Preissner S. The Transformer database: biotransformation of xenobiotics. Nucleic acids research. 2014;42:D1113-7.
[66] De Andres F, Teran S, Hernandez F, Teran E, A LL. To Genotype or Phenotype for Personalized Medicine? CYP450 Drug Metabolizing Enzyme Genotype-Phenotype Concordance and Discordance in the Ecuadorian Population. Omics : a journal of integrative biology. 2016;20:699-710.
[67] Ieiri I, Yamada S, Seto K, Morita T, Kaneda T, Mamiya K, Tashiro N, Higuchi S, Otsubo K. A CYP2D6 phenotype-genotype mismatch in Japanese psychiatric patients. Pharmacopsychiatry. 2003;36:192-6.
[68] Shiran MR, Chowdry J, Rostami-Hodjegan A, Ellis SW, Lennard MS, Iqbal MZ, Lagundoye O, Seivewright N, Tucker GT. A discordance between cytochrome P450 2D6 genotype and phenotype in patients undergoing methadone maintenance treatment. Br J Clin Pharmacol. 2003;56:220-4.
[69] Wang D, Poi MJ, Sun X, Gaedigk A, Leeder JS, Sadee W. Common CYP2D6 polymorphisms affecting alternative splicing and transcription: long-range haplotypes with two regulatory variants modulate CYP2D6 activity. Hum Mol Genet. 2014;23:268-78.
[70] Wendt FR, Sajantila A, Moura-Neto RS, Woerner AE, Budowle B. Full-gene haplotypes refine CYP2D6 metabolizer phenotype inferences. International journal of legal medicine. 2017.
[71] Pratt VM, del Tredici A, Hachad H, Ji Y, Kalman L, Scott SA, Weck KE. Recommendations for Clinical CYP2C19 Genotyping Allele Selection: A Report of teh Association for Molecular Pathology. The Journal of Molecular Diagnostics. 2018.
[72] Gillette C, Prunty L, Wolcott J, Broedel-Zaugg K. A new lexicon for polypharmacy: Implications for research, practice, and education. Research in social \& administrative pharmacy : RSAP. 2015;11:468-71.

## Supplementary Information



Figure S1. International Classification of Disease, Tenth Revision (ICD-10; see International Statistical Classification of Diseases and Related Health Problems 10th Revision - WHO Version for 2016. http://apps.who.int/classifications/icd10/browse/2016/en\#/I; accessed 21APR2017) cause of death code counts for 208 deceased tramadol-exposed Finns.


Figure S2. Association between genotype at 18 CYP2D6 loci (Table 4) and the ratio of tramadol to O-desmethyltramadol (T:M1) for $\mathrm{N}=44$ Finns. Each boxplot represents a single genotype relative to the negative DNA strand of the indicated hg19/GRCh37 chromosome 22 position; the center horizontal line represents the median, the lower and upper boundaries of each box represent the first and third quartiles, respectively; the top and bottom vertical lines indicate plus and minus three times in the interquartile range, respectively; black bots indicate boxplot outliers. A student's t-test was used to compare the mean M1:T ratio between the homozygous-reference genotype at each locus and all other genotypes observed more than once with asterisks (*) indicating $\mathrm{p}<0.05$.

Table S1. Computationally phased CYP2D6 full-gene haplotype information for 44 tramadolexposed post-mortem Finns and their associated ratio of tramadol to O-desmethyltramadol (T:M1), toxicologically-determined phenotype group (t-MP) as determined by model-based clustering (Figure 1C-E), CYP2D6 genotype-inferred metabolizer phenotype (g-MP), age, sex, and amplicon success using primers listed in Table 1 with Y and N indicating successful and unsuccessful amplification of the target, respectively.


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# CHAPTER 6 

## A Pathway-Driven Predictive Model of Tramadol Pharmacogenetics

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Frank R Wendt
Nicole MM Novroski
Anna-Liina Rahikainen
Antti Sajantila
Bruce Budowle


#### Abstract

Predicting metabolizer phenotype (MP) is typically performed using data from a single gene. Cytochrome p450 family 2 subfamily D polypeptide 6 (CYP2D6) is considered the primary gene for predicting MP in reference to approximately $30 \%$ of marketed drugs and endogenous toxins. CYP2D6 predictions have proven clinically effective but also have welldocumented inaccuracies due to relatively high genotype-phenotype discordance in certain populations. Herein, a pathway-driven predictive model employs genetic data from uridine diphosphate glucuronosyltransferase, family 1, polypeptide B7 (UGT2B7), adenosine triphosphate (ATP) binding cassette, subfamily B, number 1 (ABCB1), opioid receptor mu 1 (OPRM1), and catechol-O-methyltransferase (COMT) to predict the tramadol to primary metabolite ratio (T:M1) and the resulting toxicologically-inferred MP (t-MP). These data were then combined with CYP2D6 data to evaluate performance of a fully combinatorial model relative to CYP2D6 alone. These data identify UGT2B7 as a potentially significant explanatory marker for $\mathrm{T}: \mathrm{M} 1$ variability in a population of tramadol-exposed individuals of Finnish ancestry. Supervised machine learning and feature selection were used to demonstrate that a set of 16 loci from 5 genes can predict t-MP with over $90 \%$ accuracy, depending on t-MP category and algorithm, which was significantly greater than predictions made by CYP2D6 alone.


## Introduction

Pharmacogenetic studies typically rely on targeted monogenic genotyping approaches (i.e. detection of targeted single nucleotide variants (SNVs) from one gene) to characterize the way populations or individuals respond to drugs (1-4). The cytochrome p450 family 2 , subfamily D, polypeptide $6(C Y P 2 D 6)$ locus is a gene routinely used to predict metabolism of various compounds due to its involvement in phase I metabolism of approximately $30 \%$ of marketed drugs and endogenous toxins (3,5-8). CYP2D6 genotype-phenotype correlations have demonstrated relatively high efficacy in various clinical applications, however, notable genotype-phenotype discordance is documented (9-11). It is understood that drug ADME-R (absorption, distribution, metabolism, excretion, and response) are dependent upon protein pathways, not the activity of a single protein. Consequently, one-gene one-phenotype predictive models do not utilize extended ADME-R information. Altar, et al. demonstrated that combinatorial approaches (i.e. genetic data from multiple proteins) to predicting metabolizer phenotype (MP) have significantly more efficacious patient outcomes when compared to a single-gene single-phenotype model for psychiatric compounds $(12,13)$. Pathway-driven pharmacogenetic studies have been performed in relatively few drug classes and typically utilize relatively few loci (i.e., genes or SNVs) (14-16), but the success of this type of model has not been evaluated for extended metabolic pathways (e.g., one or two genes versus multiple genes representing various stages of ADME-R).

CYP2D6 is readily implicated in O-demethylation of tramadol to form Odesmethyltramadol (M1). Tramadol is among the most widely prescribed opioid analgesics in the United States and as such contributes to the critical public health opioid usage and distribution crisis $(17,18)$. Given the overwhelmingly high number of tramadol prescriptions
in the United States, it is essential that predictive models include as much data as possible to address the degree of CYP2D6 genotype-phenotype discordance observed in individuals and in some populations. It is reasonable to hypothesize that a combinatorial predictive model of tramadol metabolism using genetic information from proteins representative of phase II metabolism, active metabolite distribution, and neurotransmitter and analgesia propagation would provide a more complete picture of how an individual responds to tramadol.

Supervised machine learning identifies underlying relationships describing the interaction between a known outcome variable (i.e., MP) and highly dimensional explanatory variables (i.e., genotypes). To our knowledge, machine learning is not readily used to identify loci for predicting patient MP but may offer considerable advantages for pathway-driven pharmacogenetic analyses via feature selection. Herein, a pathway-driven predictive model of tramadol ADME-R was evaluated to identify features (i.e., single nucleotide [SNPs] and/or insertion/deletion [INDELs] polymorphisms) capable of classifying members of a deceased, tramadol-exposed Finnish population into toxicologically-inferred MP (t-MP) categories. The genetic data from uridine diphosphate glucuronosyltransferase, family 1, polypeptide B7 (UGT2B7), adenosine triphosphate (ATP) binding cassette, subfamily B, number 1 (ABCB1), opioid receptor mu 1 (OPRM1), and catechol-O-methyltransferase (COMT) were used in combination with CYP2D6 data (19) and demonstrate increased prediction accuracy and correlation coefficients for the t-MP and T:M1 outcome variables, respectively. These predictions were made using a substantially reduced number of loci (16 and 33 for t-MP and $\mathrm{T}: \mathrm{M} 1$, respectively) offering promise for design and clinical implementation of accurate and reproducible tramadol response models.

## Subjects and Methods

## Subjects

A total of 208 DNA samples from deceased, tramadol-exposed individuals of Finnish ancestry were used in this study. Samples were collected in Finland between 2001 and 2012 according to the ethical handling of human subjects policies at the University of Helsinki and transferred to the University of North Texas Health Science Center (Institutional Review Board protocol 2016-051). Detailed information on sample collection, toxicological analyses, and DNA extraction and quantitation were described by Wendt, et al. (19).

## Marker Selection, Library Preparation, and Massively Parallel Sequencing

A TruSeq ${ }^{\circledR}$ Custom Amplicon (TSCA) Low Input library preparation panel (Illumina ${ }^{\circledR}$, Inc.) was designed using the Illumina DesignStudio ${ }^{\mathrm{TM}}$ (see https://www.illumina.com/informatics/sample-experiment-management/custom-assaydesign.html; Accessed June 2017). The exons of four pharmacogenes (UGT2B7, ABCB1, OPRM1, and COMT) were targeted for kit design (Table 1). Library preparation was performed using 10 ng of genomic DNA and followed the manufacturer's recommended protocol. Two modifications were made to the TSCA Low Input protocol: 1) during the Remove Unbound Oligos step, sample purification beads were allowed to dry for only one minute instead of the indicated five minutes, and 2) prior to library cleanup, the hybridization plate was placed on a magnetic stand for two minutes before $45 \mu \mathrm{~L}$ of supernatant were transferred to the cleanup plate. Cleaned-up library traces were spot-checked using the Agilent 2200 TapeStation (Agilent Technologies, Waldbronn, Germany) using the Agilent 2200 High Sensitivity D1000 ScreenTape System according to the manufacturer's recommended protocol (see
https://support.illumina.com/content/dam/illuminasupport/documents/documentation/chemistry_documentation/samplepreps_truseq/truseqcust omamplicon/truseq-custom-amplicon-low-input-reference-guide-1000000002191-04.pdf;

Accessed July 2017). Sample libraries were normalized and pooled in batches of 32 and sequenced on the MiSeq (Illumina) using the MiSeq Reagent kit v2 (500 cycles) with $2 \times 250$ bp read length.

## Alignment, Variant Analysis, and Machine Learning

Resulting .fastq files were locally aligned to the hg19/GRCh37 reference genome using the Burrows-Wheeler Aligner mem command and the SamTools view, sort, and index commands (20-22). Variant calling was performed in Genome Analysis ToolKit (GATK) (23) using the HaplotypeCaller command. Resulting .vcf files were, or were converted to, standard input for VCFtools (24), Genome-wide Complex Trait Analysis (GCTA) (25), PLINK (26) IMPUTE2 v2.3.2 (ref. 27), and various in-house Excel-based workbooks.

Supervised machine learning was performed in the Waikato Environment for Knowledge Analysis (WEKA) as described previously $(28,29)$ using four classifiers: regularized multinomial logistic regression (RMLR; for t-MP only), 1-nearest neighbor (1NN; for $\mathrm{t}-\mathrm{MP}$ and $\mathrm{T}: \mathrm{M} 1$ ), random forest (RF; for $\mathrm{t}-\mathrm{MP}$ and $\mathrm{T}: \mathrm{M} 1$ ), and linear regression (LR, for T:M1 only). Feature selection and leave-one-out cross validation were used to reduce the size of the model and assess model accuracy, respectively. Note that specific descriptions of all WEKA functions used herein have been detailed previously by Wendt, et al. (19) and Schmedes, et al. $(28,29)$. Unless otherwise stated, sample n-1 (i.e., 207-fold) cross-validation was performed.

## Results

## Samples

The cohort in this study represents a larger sampling of deceased tramadol-exposed individuals of Finnish ancestry than reported previously (19). The mean ratio of tramadol to M1 (T:M1) for 208 Finns was $11.6 \pm 18.3$. There was no significant difference in mean T:M1 between males $(12.8 \pm 25.0 ; \mathrm{N}=127$; mean age 52.2 years $\pm 17.9)$ and females $(10.9 \pm 12.3$; $\mathrm{N}=81$; mean age 60.0 years $\pm 18.3$ ).

The R mclust package (30) for RStudio was used to evaluate the natural clustering of the dataset (19). Five clusters were identified and used to sort each sample into a t-MP category based on the following thresholds: poor metabolizers ( PM ; $\mathrm{T}: \mathrm{M} 1 \geq 50 ; \mathrm{N}=5$ ), intermediate metabolizers (IM; $50>\mathrm{T}: \mathrm{M} 1 \geq 20 ; \mathrm{N}=20$ ), slow normal metabolizers ( $\mathrm{NM}-\mathrm{S}$; $20>\mathrm{T}: \mathrm{M} 1 \geq 8 ; \mathrm{N}=67$ ), fast normal metabolizers (NM-F; $8>\mathrm{T}: \mathrm{M} 1 \geq 3 ; \mathrm{N}=91$ ), and ultrarapid metabolizers ( $\mathrm{UM} ; 3>\mathrm{T}: \mathrm{M} 1 \geq 1 ; \mathrm{N}=25$ ).

## Library Preparation Panel and Sequencing Performance

The massively parallel sequencing (MPS) panel targeted 216 exonic amplicons with a probe-based chemistry (Tables S1 and S2). Based on requirements for probe placement, some intronic regions also were obtained. The average amplicon length was 177 bases $\pm 6.84$. Note that $A B C B 1$ and COMT had small gaps after panel design (Table 1) resulting in lack of genotype data for two exonic SNPs (NC_000007.13:g.87133763A>G and NC_000007.13:g.87145971C>G) in $A B C B 1$, each with the alternate allele observed only once in the Exome Aggregation Consortium and 1000 Genomes Project databases (1kGP) $(31,32)$.

Sort Intolerant From Tolerant (SIFT) and Polymorphism Phenotype v-2 (PolyPhen v2) scores indicate possibly damaging consequences of NC_000007.13:g.87145971C>G (SIFT: 0; PolyPhen v2: 0.995 ) (refs. 33,34). With publically available data, there has not been any reported genetic variation in the design gap in COMT.

Table 1. Design strategy for a TruSeq Custom Amplicon Low Input library preparation panel targeting the exons of $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT. Design resulted in $98 \%$ overall coverage of desired targets. A full list of amplicons is provided in Supplemental Table $\qquad$ ; note that due to optimal amplicon sizing, certain intronic regions may have been captured within an amplicon.

| Gene | Chromosome | Amplicons* | Coverage (\%) | Gaps Coordinates | Gap Details |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{gathered} \hline U G T 2 B \\ 7 \end{gathered}$ | 4 | 24 | 100 | - | - |
| ABCB1 | 7 | 90 |  | $\begin{aligned} & 87,197,059-87,197,105 \\ & 87,198,648-87,198,648 \\ & 87,191,244-87,191,244 \\ & 87,180,975-87,180,975 \\ & 87,145,948-87,145,986 \\ & 87,133,754-87,133,770 \end{aligned}$ | Transcript NM_000927 Intron 6, Transcript NM_000927 Intron 6, Transcript NM_000927 Intron 8, Transcript NM_000927 Intron 10, Transcript NM_000927 Exon 25, Transcript NM_000927 Exon 29 |
| OPRM1 | 6 | 74 | 100 | - | - |
| COMT | 22 | 28 |  | 19,938,573-19,938,580 | Transcript NM_001135161 Exon 1 |

One pair of probes designed to target each amplicon

The average cluster density and clusters passing filter were $1159 \mathrm{k} / \mathrm{mm}^{2} \pm 290$ and $86.5 \% \pm 5.02$, respectively. Positive and negative controls performed as expected. After application of a 10X locus read-depth threshold, 8546 SNVs from $U G T 2 B 7, A B C B 1$, OPRM1 and COMT were used for feature selection and t -MP and $\mathrm{T}: \mathrm{M} 1$ prediction with an average locus read-depth of $16.4 \mathrm{X} \pm 3.60$.

## Single Nucleotide Variants

Raw .vcf files were analyzed in VCFtools to generate population genetic summary statistics based on a minimum read-depth threshold of 10X. The average alternate allele frequency of 8546 SNVs was $0.0300 \pm 0.0876$. After Bonferroni correction ( $\mathrm{p}_{\text {adj_heterozygous_loci }}$
$=3.59 \times 10^{-5} ; \sim 70$ deviations expected due to chance alone), 8 loci significantly deviated from expectations of Hardy-Weinberg Equilibrium (NC_000004.11:g.69964180C>T, NC_000004.11:g.69978750C>T, NC_000006.11:g.154414563A>G, NC_000006.11:g.154414573C>T, NC_000006.11:g.154428702A>C, NC_000007.13:g.87178626C>T, NC_000007.13:g.87180198A>C, and NC_000022.10:g.19956781G>A), all of which exhibited significant excess heterozygosity in this Finnish population. This suggests that there was relatively little population substructure in this cohort (mean difference between observed and expected heterozygotes of $30.2 \pm 8.16$ ).

Linkage disequilibrium (LD) was evaluated in VCFtools using the genotype pairs from SNVs within UGT2B7, ABCB1, OPRM1, COMT, and CYP2D6 ( $\mathrm{N}=10421$ ). Note that CYP2D6 genotype data used in this study are those generated by Wendt, et al. (19) for a subset of the 208 Finns $(N=44)$ described here and are not analyzed independently herein. A total of 2252 significant pairwise LDs between SNVs in different genes was observed ( $\mathrm{p}_{\text {adj }}=9.21 \mathrm{x}$ $10^{-10}$ ); of these, 8 SNV pairs had $\geq 25$ individuals (i.e., 50 alleles) contributing to the LD pattern with $r^{2}$ values $\geq 0.65$ (Table 2; mean $r^{2}=0.957 \pm 0.122$ ).

Table 2. Significant pairwise linkage disequilibria (LD; padj $<9.21 \times 10^{-10}$ ) between single nucleotide variants (SNVs) in different genes of interest for only those pairs of SNVs with at least 25 genotypes (i.e., 50 alleles) contributing to the LD pattern and $\mathrm{r}^{2}$ values $\geq 0.65$.

| Locus 1 (hg19/GRCh37) | rs Number (Locus 1) | Locus 2 (hg19/GRCh37) | rs Number (Locus 2) | $\mathbf{r}^{2}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| NC_000004.11:g.69962282G>A | - | NC_000006.11:g.154360666C>T | rs199648369 | 0.656 |
| NC_000004.11:g.69978303C>G | - | NC_000007.13:g.87214698A>G | - | 1 |
| NC_000004.11:g.69962733C>T | - | NC_000006.11:g.154412616T>A | - | 1 |
| NC_000004.11:g.69962733C>T | - | NC_000006.11:g.154360678C>A | rs1297476429 |  |
| NC_000004.11:g.69962676C>T | rs14712761 | NC_000007.13:g.87224929T>C | - | 1 |
| NC_000004.11:g.69963152T>C | rs1386213886 | NC_000007.13:g.87214721G>A | - | 1 |
| NC_000004.11:g.69963152T>C | rs1386213886 | NC_000006.11:g.154412881A>C | - | 1 |
| NC_000004.11:g.69962733C>T | - | NC_000007.13:g.87224962 T>C | - | 1 |

Individual SNVs were correlated with T:M1 using Pearson's correlation (Figure 1A) with genotype imputation for missing loci. After correction for multiple testing ( $\mathrm{p}_{\text {adj }}=2.42 \mathrm{x}$ $10^{-6}$ ), 14 SNVs were significantly associated with the rate of tramadol O-demethylation (Table 3). Two pairs of loci exhibited significant LDs (NC_000007.13:g.87229006T>G/NC_000022.10:g.19938432G>A $\quad[\mathrm{N}=164$ and 147 genotypes, respectively] and NC_000004.11:g.69972849T>C/ NC_000022.10:g.19938432G>A [ $\mathrm{N}=150$ and 147 genotypes, respectively]).

The heritability ( $\mathrm{h}^{2}$ ) of t-MP and T:M1 was inferred using the --reml command in GATK with individual and pairwise combinations of two, three, four, and all five genes (Figure 1B). In general, the variability of $t-M P$ was poorly explained regardless of gene or gene combination. However, after correction for multiple testing ( $\mathrm{p}_{\text {adj }}=0.00161$ ), the SNVs from UGT2B7 $\left(\mathrm{h}^{2} T: M 1=0.821 ; \mathrm{p}=1.22 \times 10^{-6}\right)$ and the combination of SNVs from CYP2D6/UGT2B7 $\left(\mathrm{h}^{2}{ }_{T: M 1}=0.786 ; \mathrm{p}=4.04 \times 10^{-4}\right)$ significantly explained relatively large proportions of the variation in T:M1 with relatively little error (0.0594 and 0.0758 for UGT2B7 and CYP2D6/UGT2B7, respectively).


Figure 1. (A) Association between the tramadol to O-desmethyltramadol ratio (T:M1) for individual genotypes at UGT2B7, ABCB1, OPRM1, and COMT. A dashed horizontal line indicates the threshold for significance after correction for multiple testing $\left(-\log _{10}\left(\mathrm{p}_{\mathrm{adj}}\right)=5.62\right)$; loci are labeled if they exceed the significance threshold and have regression coefficients $\geq$ 0.45 (arbitrarily selected to avoid locus label overlap). (B) Heritability summary of restricted maximum likelihood (--reml in GCTA) analyses, with the first 20 eigenvectors as covariates, of the T:M1 (solid black circles) and the associated toxicologically-inferred metabolizer-phenotype (t-MP; solid grey triangles) phenotypes. A dashed horizontal line indicates the threshold for significance after correction for multiple testing $\left(-\log _{10}\left(\mathrm{p}_{\mathrm{adj}}\right)=2.79\right)$; two data points are labeled, indicating that the individual (UGT2B7) and combined (CYP2D6/UGT2B7) genotype information significantly explained a relatively high proportion of phenotypic variance.

Table 3. Relevant locus information for fourteen loci significantly associated with the tramadol to O-desmethyltramadol ratio (T:M1) in 208 autopsied individuals from a Finnish population sample.

| $\underset{\substack{\text { Chr } \\ \text { (Gene) }}}{ }$ | rs | hg19/GRCh37 | cDNA Position | hg38/GRCh38 | cdNa Position | $\begin{gathered} \Delta \text { Base } \\ \text { (RePAlt) } \end{gathered}$ | $\begin{gathered} \Delta \\ \text { Amino } \\ \text { Acid } \end{gathered}$ | $\begin{gathered} \text { Pearson's r} \pm \text { s.e. } \\ (95 \% \mathrm{CI}) \end{gathered}$ | p | $\begin{gathered} \text { CADD } \\ \text { (Phrred) } \end{gathered}$ | $\begin{gathered} \text { SIFT } \\ \text { (Score) } \end{gathered}$ | PolyPhen (Score) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ${ }_{(U G T 2 B 7)}^{4}$ | rs1255338508 | NC_000004.11:.69962349 | XM_005265702.1:C.-26-1909; | NC_000004.12:g.69996631 | $\begin{aligned} & \text { NM_001074.3:c.111; } \\ & \text { NM_001330719.1..11; } \\ & \text { XM_011532229.c. } 1111 \end{aligned}$ | ¢>T | m | $\begin{gathered} 0.563 \pm 0.0585 \\ (0.448-0.678) \end{gathered}$ | $2.56 \times 10^{-18}$ | 0.00400 | Tolerated $(0.990)$ | $\begin{gathered} \text { Benign } \\ (0.0100) \end{gathered}$ |
| $\stackrel{4}{(U G T 2 B 7)}$ | - | NC_000004.11:.69978334 | XM_005265702.1:c. 723 ; NM_001074.2:. 1470 | NC_000004. 12:g. 69112616 | NM_001349568.1:c.723; NM_001074.3:c. 1470 NM 001330719.1:c. ${ }^{* 140}$ | TDC | s>8 | $\underset{(0.328-0.587)}{0.488 \pm 0.061}$ | $7.09 \times 10^{.11}$ | 0.00500 | - | - |
| $\stackrel{4}{(U G T 2 B)}$ | - | NC_000004.11:g69972849 | $\begin{aligned} & \text { XM_005265702.1:c.256-44; } \\ & \text { NM_001074.2: } 1003-44 \end{aligned}$ | NC_000004.12:g.69107131 |  | T>C | Intron | $\begin{aligned} & 0.367 \pm 0.0720 \\ & (0.226-0.508) \end{aligned}$ | $1.02 \times 10^{-6}$ | 1.01 | - | - |
| $\begin{gathered} (\text { OPRMI) } \end{gathered}$ | - | NC_000006.11:g. 154439986 | NM_001145279.2:c.*130; <br> NM_001145280.2:c.*130 <br> NM 001145281.1:c.*130 <br> NM_001008503.1:c.1164+27379; <br> NM_000914.3 :c.*130; <br> NM_001145287.1:c.*130 <br> XM_005267003.1:c.*130 | NC_000006.12:.154118851 |  | delTT | - | $\begin{gathered} 0.593+0.0564 \\ (0.483-0.040) \end{gathered}$ | $6.08 \times 10^{221}$ | 9.00 | - | - |
| 7 (ABCBI) | - | NC_000007.13:8.872 14994 | NM_000927.4.c. 120 | NC_000007. 14:8.87585678 | NM_001348944.1:c. 120; NM 000927.4.c. 120; NM_001348946.1:c. 12 NM ${ }^{\text {NM }}$-001348945.1.c.330 | ${ }^{\text {A }}$ ¢ | F>F | $0.531 \pm 0.0593$ $(0.415-0.647)$ | $1.97 \times 10^{-16}$ | 15.7 | - | - |
| 7 (ABCBI) | - | NC_000007.13:9.87229912 |  | NC_000007.14:8.87600596 | - | C>T | - | $0.544 \pm 0.0633$ <br> (0.420-0.668) | $4.71 \times 10^{-15}$ | 11.4 | - | - |
| 7 (ABCBI) | - | NC_000007.13:8.87224837 | NM__00927.4.c. 117+245 | NC_000007.14:8.87995521 | - | ${ }^{>} \times$ | - | $\begin{aligned} & 0.562+0.0587 \\ & (.0447-0.677) \end{aligned}$ | $3.07 \times 10^{1 / 4}$ | 2.46 | - | - |
| 7 (ABCBI) | - | NC_000007.13:8.87230159 | NM_000977.4.c. 95 | NC_000007.14:8.87600843 | NM_000927.4.c.-95; | c>A | - | $\begin{aligned} & 0.473 \pm 0.0616 \\ & (0.352-0.593) \end{aligned}$ | $6.8 \times 10^{-13}$ | ${ }^{13.1}$ | - | - |
| 7 (ABCBI) | rs569567574 | NC_000007.13:8.87178819 | NM_000927.4.c. 1570 | NC_000007.14:8.87549903 |  | C>T | $\mathrm{v}>1$ | $0.446 \pm 0.0659$ $(0.317-0.575)$ | $1.66 \mathrm{x} 10^{-10}$ | 28.3 | $\underset{(0)}{\text { Deleterious }}$ | Probably Damaing $(0.878)$ |
| 7 (ABCBI) | rs1380760525 | NC_000007.13:8.872 29006 | NM_000927.4.c.688+427 | NC_000007.14:8.87599690 | - | ${ }^{\text {T }}$ G | - | $0.452 \pm 0.0692$ (0.316-0.587) | $7.73 \times 10^{-10}$ | 0.7 | - | - |
| 7 (ABCBI) | - | NC_000007.13:8.87179932 | NM_000927.4.c. 1305 | NC_000007. 14:8.87550216 | NM_001348944.1:c. 1305; NM_000927.4.c. 1305; NM_001348945.1:c.1515; | T>C | T>T | $\begin{aligned} & 0.405 \pm 0.0639 \\ & (0.280-0.530) \end{aligned}$ | $1.52 \times 10^{-9}$ | 0.0330 | - | - |
| 7 (ABCBI) | - | NC_000007.13:8.87135183 | NM_-000927.4.c.3636+30 | NC_000007.14:8.87505867 | - | ${ }^{\text {A }}$ ¢ | - | $\begin{aligned} & 0.311 \pm 0.0475 \\ & (.0218 .0 .40) \end{aligned}$ | $2.75 \times 10^{-9}$ | 9.01 | - | - |
| 7 (ABCBI) | - | NC_000007. 13:8.87179342 | NM_000927.4.c. 1379 | NC_000007. 14:8.87550026 |  | ¢>T | T N | $\underset{(0.261-0.518)}{0.3900 .056}$ | $1.29 \times 10^{-8}$ | 18.8 | Tolerated (0.0900) | Benign $(0.0217)$ |
| $\begin{gathered} 22 \\ (\text { com }) \end{gathered}$ | - | NC_000022.10:g.19938432 | - | NC_000022.11:g.19950909 | - | G>A | - | $\begin{array}{r} 0.367 \pm 0.0726 \\ (0.225-0.510) \end{array}$ | $1.14 \times 10^{-6}$ | 1.28 | - | - |

## Predicting $t-M P$

Predictions of t-MP and T:M1 were performed in two phases: 1) classification of MP using combined unphased genotype data from UGT2B7, ABCB1, OPRM1, and COMT, and 2) classification with computationally phased genotypes from the same four genes. In general, unphased genotypes predicted t-MP and T:M1 variables with less accuracy and lower correlation coefficients than the phased genotype models. The results presented herein focus on predictions of t-MP and T:M1 using phased genotype data.

The 208 tramadol-exposed individuals of Finnish ancestry used for classification represent five classes of t -MP. Using three supervised machine learning models, t -MP prediction accuracies were relatively low with mean accuracies of $19.2 \% \pm 39.7$ (RF), $20.4 \%$ $\pm 23.0(1 \mathrm{NN})$, and $25.2 \% \pm 15.6$ (RMLR) which are not better than random chance ( $20.9 \%$, $10 \%$-trimmed mean). These accuracies represent poor prediction of all five t-MPs, with lack of a true positive prediction for the $\mathrm{t}-\mathrm{IM}$ and $\mathrm{t}-\mathrm{PM}$ categories in all three models. Overall, the RMLR classifier predicted t-MP with significantly higher accuracies than the 1 NN or RF classifiers ( $\mathrm{p}<0.001$ ).

Feature selection was used to evaluate classification accuracies as a reduced number of SNVs are provided for each model. The models were evaluated with features used in $>0 \%$, $>12 \%,>25 \%,>50 \%$, and $>75 \%$ of cross-validation folds (Figure 2). Classification accuracies generally increased for all five t-MP categories with the RMLR classifier outperforming the LR and 1 NN models. RMLR predicted the t -MP variable with mean accuracies for t - UM , t -NM-F, t-NM-S, and t-IM that were 1.22- ( $25.6 \% \pm 2.19$ ), $3.35-(70.1 \% \pm 2.38), 2.64-(55.2 \%$ $\pm 4.47)$ and 2.01 -fold $(42.0 \% \pm 2.74)$ greater than random chance $(20.9 \% ; 10 \%$-trimmed mean), respectively. Note that t-PMs were not reliably predicted with any algorithm.


Figure 2. Summary of machine learning classification accuracies for four metabolizer phenotype clusters ( $\mathrm{t}-\mathrm{UM}=$ ultra-rapid; $\mathrm{t}-\mathrm{NM}-\mathrm{F}=$ normal/extensive $[$ fast]; $\mathrm{t}-\mathrm{NM}-\mathrm{S}=$ normal/extensive [slow]; and t-IM = intermediate) using phased UGT2B7, ABCB1, OPRM1, and COMT data aligned to the hg19/GRCh37 reference genome for varying feature selection stringencies (features used in greater than $0 \%, 12 \%, 25 \%, 50 \%$, and $75 \%$ of cross-validation folds) compared to the accuracy of the model using all genotype data from $U G T 2 B 7, A B C B 1$, OPRM1, and COMT. Three machine learning algorithms are depicted: 1-nearest neighbor (1NN), random forest (RF), and regularized multinomial logistic regression (RMLR); dashed lines represent the average predictive accuracy due to random chance ( $20.9 \%$; $10 \%$-trimmed mean).

Wendt, et al. (19) previously described t-MP classification using CYP2D6 alone. That study analyzed a subset of the current sample set ( $\mathrm{N}=44 / 208$ individuals) which had genetic data for a fully comprehensive t-MP prediction. Note that because of limited sampling, this cohort represented only four MP categories (i.e., t-PMs were not observed) and used 43 -fold cross validation. Using a comprehensive, pathway-driven model with all 10421 SNVs from CYP2D6 (19), UGT2B7, ABCB1, OPRM1, and COMT, performance of the RF, 1NN, and RMLR classifiers modestly increased to $27.3 \%, 27.3 \%$, and $20.5 \%$, respectively. Feature selection increased these classification accuracies with the RMLR classifier again
outperforming the 1 NN and RF models in overall accuracy (mean of $60.6 \% \pm 19.1$ overall; $61.5 \%$ for $\mathrm{t}-\mathrm{UM}, 75.0 \%$ for $\mathrm{t}-\mathrm{NM}-\mathrm{F}, 72.7 \%$ for $\mathrm{t}-\mathrm{NM}-\mathrm{S}$, and $33.3 \%$ for $\mathrm{t}-\mathrm{IM}$; Figure 3A). Relative to the CYP2D6 predictions, the pathway-driven model using CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT together provided significantly higher classification accuracies for t-MP ( $\mathrm{p}=0.0190$; paired t -test $)$. The maximum classification accuracy reached $93.8 \%$ using only 16 SNVs.


Figure 3. Summary of machine learning classification accuracies for metabolizer phenotype $(t-U M=$ ultra-rapid; $\mathrm{t}-\mathrm{NM}=$ normal/extensive, and $\mathrm{t}-\mathrm{IM}=$ intermediate; panel A$)$ and the tramadol to O-desmethyltramadol ratio (T:M1; panel B) using phased CYP2D6 (unpublished data), UGT2B7, ABCB1, OPRM1, and COMT data aligned to the hg19/GRCh37 reference relative to using CYP2D6 alone. In panel A, varying feature selection stringencies (i.e., features used in greater than $0 \%, 12 \%, 25 \%, 50 \%$, and $75 \%$ of cross-validation folds) and supersized machine learning algorithms (i.e., 1-nearest neighbor (1NN), random forest (RF), and regularized multinomial logistic regression (RMLR)) were used.; dashed lines represent the average predictive accuracy due to random chance ( $39.9 \%$ for pathway model and $23.8 \%$ for CYP2D6 model; $10 \%$-trimmed mean). Note the cube root scale in panel B with standard error shown in grey shading along the length of each robust linear regression.

## Predicting T:M1

Supervised machine learning was performed on the T:M1 outcome variable in the same manner as t-MP except that the LR classifier was used instead of RMLR. The average difference between actual and predicted T:M1 ( $\Delta \mathrm{T}: \mathrm{M} 1$ ) using 8,546 phased SNVs from $U G T 2 B 7, A B C B 1, O P R M 1$, and $C O M T$ was $-1.54 \pm 17.6$, indicating overall underestimation of T:M1. The 1NN classifier underestimated T:M1 with significantly greater magnitude than the RF and LR classifiers ( $\mathrm{p}<1 \times 10^{-20}$ ) with mean $\Delta \mathrm{T}: \mathrm{M} 1$ of $-5.89 \pm 18.9(1 \mathrm{NN}), 0.191 \pm$ 19.0 (LR), and $-0.581 \pm 18.8(\mathrm{RF})$.

The same five feature inclusion thresholds were evaluated for the T:M1 variable (Figure 4). Overall, T:M1 was modestly predicted regardless of feature-inclusion stringency or supervised machine learning algorithm used. The average correlation coefficients between actual and predicted T:M1 were not significantly different regardless of feature-inclusion stringency; however, the correlation coefficients from the LR classifier ( $\mathrm{r}^{2}=0.113 \pm 0.0212$ ) were significantly lower than those of the $1 \mathrm{NN}\left(\mathrm{r}^{2}=0.277 \pm 0.0520\right)$ and $\mathrm{RF}\left(\mathrm{r}^{2}=0.284 \pm\right.$ 0.0307 ) classifiers. The maximum observed correlation coefficient was 0.383 with the 1 NN classifier.

T:M1 predictions with CYP2D6 alone and the pathway-driven model were evaluated. For 44 samples and the full set of genotype data without feature selection $\left(\mathrm{N}_{\mathrm{SNV}_{\mathrm{s}}}=10421\right)$, the pathway-driven model (mean $\Delta \mathrm{T}: \mathrm{M} 1-1.35 \pm 12.8$ ) yielded a significantly lower $\Delta \mathrm{T}: \mathrm{M} 1$ than the CYP2D6 model (mean $\Delta \mathrm{T}: \mathrm{M} 1=-6.79 \pm 34.9 ; \mathrm{p}=0.0293$ ). This observation was especially true for the LR classifier $\left(\Delta \mathrm{T}: \mathrm{M} 1_{\text {pathway }}=-0.101 \pm 12.3\right.$ and $\Delta \mathrm{T}: \mathrm{M} 1_{\text {CYP2D6 }}=-20.1 \pm$ 56.2 ) which had a significantly decreased $\Delta \mathrm{T}$ : M1 with the pathway-driven model ( $\mathrm{p}<0.01$ ). Note that the 1 NN classifier performed less well with pathway-driven data ( $\Delta \mathrm{T}: \mathrm{M} 1=-4.40 \pm$
13.6) relative to the $C Y P 2 D 6$ data ( $\triangle \mathrm{T}: \mathrm{M} 1=-1.10 \pm 14.3$ ). This observation holds true for the LR classifier using the $>12 \%,>25 \%,>50 \%$, and $>75 \%$ feature inclusion thresholds with significant improvements of the pathway-driven models relative to the equivalent featureinclusion model using CYP2D6 alone ( $\mathrm{p}<0.00330$ ).



$$
\text { InclusionStringency }>0 \bullet>12 \bullet>25 \bullet>50 \bullet>75 \text { Method } \bullet 1 N N \& L R \text { RF }
$$

Figure 4. Summary of tramadol O-demethylation (T:M1 ratio) predictions using three supervised machine learning algorithms (1-nearest neighbor [1NN], linear regression [LR], and random forest $[\mathrm{RF}]$ ) and five feature-inclusion criteria (i.e., features included in $>0 \%$, > $12 \%,>25 \%,>50 \%$, and $>75 \%$ of cross-validation folds) relative to the prediction using genotype data from 8,546 loci in UGT2B7, OPRM1, ABCB1, and COMT for phased and unphased hg19/GRCh37 data. The dashed lines represent the average predictive accuracy due to random chance ( $0.112 ; 10 \%$-trimmed mean). The individual data points contributing to these correlation coefficients are shown in Figure S1.

## Discussion

This study evaluated a combinatorial, pathway-driven pharmacogenetic model of tramadol O-demethylation using a custom TSCA Low Input library preparation panel targeting the exons of UGT2B7, ABCB1, OPRM1, and COMT, which are responsible for various stages of tramadol ADME-R. Note that while exons were targeted for panel design, optimization of amplicon size involved capturing some intronic loci. While not specifically interrogated here, there are intronic, promoter, enhancer, and/or silencer SNVs that have been implicated in variable gene expression, splicing, and/or post-translational modifications that need to be explored further to develop fully pathway-driven models of drug-specific and drug-class ADME-R.

Fourteen SNVs were significantly associated with T:M1; however, only one of these (NC_000007.13:g.87178819C>T) was predicted to alter protein function by causing a valine to isoleucine amino acid change adjacent to the ATP-binding cassette signature sequence, between the signature and Q-loop. This locus was observed with an allele frequency of 0.000200 in the 1 kGP (South Asian super-population only) but was not present in the Sequencing Initiative Suomi (SISu; Finnish population only; see Sequencing Initiative Suomi project (SISu), Institute for Molecular Medicine Finland, University of Helsinki, Finland. URL: http://sisuproject.fi [SISu v4.1, May, 2018]). Combined Annotation Dependent Depletion (CADD) indicates this locus as one of the top 0.1-1\% most deleterious substitutions in the human genome with SIFT and PolyPhen-v2 providing agreeable predictions (33-35). Its position within the binding pocket of ABCB 1 is quite close to cross linked regions of the domain; though charge is not disrupted by the change of valine to isoleucine, the extra methyl
group of isoleucine may sterically hinder appropriate cross-linking between nucleotide binding domains 1 and 2 (refs. 36-38).

The t-MP variable was relatively poorly explained by the genetic data from CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT (10 421 SNVs) with restricted maximum likelihood analysis for all combinations of genes (i.e., singlets, pairs, trios, etc.). Interestingly, T:M1 was highly explained by genetic variation at $U G T 2 B 7$ and the combination of $U G T 2 B 7-C Y P 2 D 6$, which was likely an artifactual inflation of the poor explanation of T:M1 by CYP2D6 relative to $U G T 2 B 7$. This is an interesting observation since CYP2D6 data alone are routinely relied upon for predicting drug response. CYP2D6 information is typically used as a predictor for the ratio of drug concentration to active metabolite concentration (1,4,5,39,40), thereby guiding safer first-pass drug doses in place of solely trial-and-error. While CYP2D6 is considered a front-end indicator of drug to metabolite ratio, UGT2B7 is responsible for efficient glucuronidation of the metabolite, facilitating its biliary excretion. Increased or decreased activity of UGT2B7 may be associated with fast or slow excretion of a metabolite, respectively, influencing patient outcomes (i.e. slow glucuronidation of morphine via UGT2B7 may result in accumulation of morphine and its associated toxicity). The data herein suggest that UGT2B7 may serve as an equally, or more, informative back-end indicator of the same phenotype predicted frequently by CYP2D6.

Three supervised machine learning algorithms were used to predict t-MP and T:M1. In general, t-MP was predicted well using the combination of $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT genotype information. Classification accuracies were especially high for the $\mathrm{t}-\mathrm{NM}-\mathrm{F}$ and t -NM-S categories, demonstrating reliable detection of normal versus non-normal metabolizers. Predicting the direction of non-normality was less successful; however, the
highest feature inclusion stringency increased classification accuracies of the t-UM, t-IM, and t -PM categories. Overall, t-PM was poorly predicted with these SNVs using all three models. It is important to note that this MP is regularly characterized by a variety of structural aberrations and while SNV predictions may have been poor, large cohorts of known PMs may enable SNV models in the absence of structural information. T:M1 was poorly predicted using the three selected algorithms; however, predicting this outcome variable was noticeable, and significantly, algorithm dependent. While using multiple machine learning algorithms and feature inclusion criteria may be seen as biased, this approach may be beneficial for future application and possible best practices for clinical implementation of predictive models based on genotyping approaches. The data presented using a pathway-driven predictive model of tramadol ADME-R demonstrated clear algorithm differences with the RF and 1NN classifiers exhibiting the highest correlation coefficients between predicted and actual T:M1. While the RF classifier produced some of the highest t -MP prediction accuracies, it failed to reliably predict the extreme categories (i.e., $\mathrm{t}-\mathrm{PM}, \mathrm{t}-\mathrm{IM}$, and $\mathrm{t}-\mathrm{UM}$ ); on the other hand, the RMLR classifier predicted t-MP quite well across a range of categories.

A subset of samples were assayed in a truly combinatorial fashion, with full genotype data for CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT. By applying the RMLR, 1NN, RF, and LR classifiers to this subset of samples, it was demonstrated that a pathway-driven model of tramadol ADME-R more accurately predicts outcome than a CYP2D6-driven model. The predictive models presented here for T:M1 and t-MP achieved high accuracies depending on category and algorithm used; however, the power of this approach is represented by the number of loci used to predict either outcome variable. Relative to a model using 10,421 SNVs (maximum accuracy of $68.8 \%$ ), t-MP can be predicted with up to $93.8 \%$ accuracy using 16

SNVs (651-fold reduction in SNVs) and T:M1 can be predicted with a correlation coefficient up to 0.329 with 33 SNVs (316-fold reduction in SNVs; Table 4).

A pathway-driven predictive model was applied to tramadol ADME-R in this study and similar approaches can be applied to other opioids or the general opioid analgesic drug class. It is likely that a more broadly applicable predictive model will employ supplementary DNA elements (i.e., introns, promoters, enhancers, silencers, distant regulatory elements, etc.), and the data described here demonstrate feasibility of pathway-driven models such that additional DNA elements may be explored and exploited for development of relatively small, accurate, and easily implemented MPS library preparation kits for clinical application of drug response models.

Table 4. Relevant locus information for 16 and 33 loci used to predict the tramadol to Odesmethyl tramadol ratio (T:M1) and the toxicologically-inferred metabolizer phenotype (tMP) at the most stringent feature inclusion threshold (i.e., all listed single nucleotide variants were used in $>75 \%$ of supervised machine learning cross-validation folds).


## References

1. Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2017;19(1):69-76.
2. Ingelman-Sundberg M. Genetic polymorphisms of cytochrome P450 2D6 (CYP2D6): clinical consequences, evolutionary aspects and functional diversity. Pharmacogenomics J. 2005;5(1):6-13.
3. Leppert W. CYP2D6 in the metabolism of opioids for mild to moderate pain. Pharmacology. 2011;87(5-6):274-85.
4. Sistonen J, Fuselli S, Palo JU, Chauhan N, Padh H, Sajantila A. Pharmacogenetic variation at CYP2C9, CYP2C19, and CYP2D6 at global and microgeographic scales. Pharmacogenet Genomics. 2009;19(2):170-9.
5. Koski A, Sistonen J, Ojanpera I, Gergov M, Vuori E, Sajantila A. CYP2D6 and CYP2C19 genotypes and amitriptyline metabolite ratios in a series of medicolegal autopsies. Forensic Sci Int. 2006;158(2-3):177-83.
6. Levo A, Koski A, Ojanpera I, Vuori E, Sajantila A. Post-mortem SNP analysis of CYP2D6 gene reveals correlation between genotype and opioid drug (tramadol) metabolite ratios in blood. Forensic Sci Int. 2003;135(1):9-15.
7. Mas S, Gasso P, Torra M, Bioque M, Lobo A, Gonzalez-Pinto A, et al. Intuitive pharmacogenetic dosing of risperidone according to CYP2D6 phenotype extrapolated from genotype in a cohort of first episode psychosis patients. European neuropsychopharmacology : the journal of the European College of Neuropsychopharmacology. 2017;27(7):647-56.
8. Susce MT, Murray-Carmichael E, de Leon J. Response to hydrocodone, codeine and oxycodone in a CYP2D6 poor metabolizer. Prog Neuropsychopharmacol Biol Psychiatry. 2006;30(7):1356-8.
9. De Andres F, Teran S, Hernandez F, Teran E, A LL. To Genotype or Phenotype for Personalized Medicine? CYP450 Drug Metabolizing Enzyme Genotype-Phenotype Concordance and Discordance in the Ecuadorian Population. Omics : a journal of integrative biology. 2016;20(12):699-710.
10. Gaedigk A, Bradford LD, Marcucci KA, Leeder JS. Unique CYP2D6 activity distribution and genotype-phenotype discordance in black Americans. Clin Pharmacol Ther. 2002;72(1):76-89.
11. Shiran MR, Chowdry J, Rostami-Hodjegan A, Ellis SW, Lennard MS, Iqbal MZ, et al. A discordance between cytochrome P450 2D6 genotype and phenotype in patients undergoing methadone maintenance treatment. Br J Clin Pharmacol. 2003;56(2):220-4.
12. Altar CA, Carhart J, Allen JD, Hall-Flavin D, Winner J, Dechairo B. Clinical Utility of Combinatorial Pharmacogenomics-Guided Antidepressant Therapy: Evidence from Three Clinical Studies. Molecular neuropsychiatry. 2015;1(3):145-55.
13. Altar CA, Carhart JM, Allen JD, Hall-Flavin DK, Dechairo BM, Winner JG. Clinical validity: Combinatorial pharmacogenomics predicts antidepressant responses and healthcare utilizations better than single gene phenotypes. Pharmacogenomics J. 2015;15(5):443-51.
14. Baber M, Chaudhry S, Kelly L, Ross C, Carleton B, Berger H, et al. The pharmacogenetics of codeine pain relief in the postpartum period. Pharmacogenomics J. 2015;15(5):430-5.
15. Bastami S, Gupta A, Zackrisson AL, Ahlner J, Osman A, Uppugunduri S. Influence of UGT2B7, OPRM1 and ABCB1 gene polymorphisms on postoperative morphine consumption. Basic \& clinical pharmacology \& toxicology. 2014;115(5):423-31.
16. Sistonen J, Madadi P, Ross CJ, Yazdanpanah M, Lee JW, Landsmeer ML, et al. Prediction of codeine toxicity in infants and their mothers using a novel combination of maternal genetic markers. Clin Pharmacol Ther. 2012;91(4):692-9.
17. Seya MJ, Gelders SF, Achara OU, Milani B, Scholten WK. A first comparison between the consumption of and the need for opioid analgesics at country, regional, and global levels. Journal of pain \& palliative care pharmacotherapy. 2011;25(1):6-18.
18. Solanki DR, Koyyalagunta D, Shah RV, Silverman SM, Manchikanti L. Monitoring opioid adherence in chronic pain patients: assessment of risk of substance misuse. Pain physician. 2011;14(2):E119-31.
19. Wendt F, Novroski, NMM, Rahikainen AL, Sajantila A, Budowle B. Supervised classification of CYP2D6 metabolizer phenotype with tramadol-exposed Finns. International Journal of Legal Medicine. Submitted 01JUN2018.
20. LiH . A statistical framework for SNP calling, mutation discovery, association mapping and population genetical parameter estimation from sequencing data. Bioinformatics (Oxford, England). 2011;27(21):2987-93.
21. Li H, Durbin R. Fast and accurate short read alignment with Burrows-Wheeler transform. Bioinformatics (Oxford, England). 2009;25(14):1754-60.
22. Li H, Handsaker B, Wysoker A, Fennell T, Ruan J, Homer N, et al. The Sequence Alignment/Map format and SAMtools. Bioinformatics (Oxford, England). 2009;25(16):20789.
23. McKenna A, Hanna M, Banks E, Sivachenko A, Cibulskis K, Kernytsky A, et al. The Genome Analysis Toolkit: a MapReduce framework for analyzing next-generation DNA sequencing data. Genome research. 2010;20(9):1297-303.
24. Danecek P, Auton A, Abecasis G, Albers CA, Banks E, DePristo MA, et al. The variant call format and VCFtools. Bioinformatics (Oxford, England). 2011;27(15):2156-8.
25. Yang J, Lee SH, Goddard ME, Visscher PM. GCTA: a tool for genome-wide complex trait analysis. Am J Hum Genet. 2011;88(1):76-82.
26. Purcell S, Neale B, Todd-Brown K, Thomas L, Ferreira MA, Bender D, et al. PLINK: a tool set for whole-genome association and population-based linkage analyses. Am J Hum Genet. 2007;81(3):559-75.
27. Howie BN, Donnelly P, Marchini J. A flexible and accurate genotype imputation method for the next generation of genome-wide association studies. PLoS genetics. 2009;5(6):e1000529.
28. Schmedes SE, Woerner AE, Budowle B. Forensic human identification using skin microbiomes. Applied and environmental microbiology. 2017.
29. Schmedes SE, Woerner AE, Novroski NMM, Wendt FR, King JL, Stephens KM, et al. Targeted sequencing of clade-specific markers from skin microbiomes for forensic human identification. Forensic science international Genetics. 2018;32:50-61.
30. Scrucca L, Fop M, Murphy TB, Raftery AE. mclust 5: Clustering, Classification and Density Estimation Using Gaussian Finite Mixture Models. The R journal. 2016;8(1):289-317.
31. Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, Korbel JO, et al. A global reference for human genetic variation. Nature. 2015;526(7571):68-74.
32. Lek M, Karczewski KJ, Minikel EV, Samocha KE, Banks E, Fennell T, et al. Analysis of protein-coding genetic variation in 60,706 humans. Nature. 2016;536(7616):285-91.
33. McLaren W, Gil L, Hunt SE, Riat HS, Ritchie GR, Thormann A, et al. The Ensembl Variant Effect Predictor. Genome biology. 2016;17(1):122.
34. McLaren W, Pritchard B, Rios D, Chen Y, Flicek P, Cunningham F. Deriving the consequences of genomic variants with the Ensembl API and SNP Effect Predictor. Bioinformatics (Oxford, England). 2010;26(16):2069-70.
35. Kircher M, Witten DM, Jain P, O'Roak BJ, Cooper GM, Shendure J. A general framework for estimating the relative pathogenicity of human genetic variants. Nature genetics. 2014;46(3):310-5.
36. Dhaliwal AK, Mohan A, Gill KS. Comparative analysis of ABCB1 reveals novel structural and functional conservation between monocots and dicots. Frontiers in plant science. 2014;5:657.
37. Loo TW, Bartlett MC, Clarke DM. The "LSGGQ" motif in each nucleotide-binding domain of human P-glycoprotein is adjacent to the opposing walker A sequence. The Journal of biological chemistry. 2002;277(44):41303-6.
38. Sauna ZE, Ambudkar SV. About a switch: how P-glycoprotein (ABCB1) harnesses the energy of ATP binding and hydrolysis to do mechanical work. Molecular cancer therapeutics. 2007;6(1):13-23.
39. Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS. The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther. 2008;83(2):234-42.
40. Sistonen J, Sajantila A, Lao O, Corander J, Barbujani G, Fuselli S. CYP2D6 worldwide genetic variation shows high frequency of altered activity variants and no continental structure. Pharmacogenet Genomics. 2007;17(2):93-101.

## Supplementary Information



Figure S1. Summary of machine learning predicted tramadol:O-desmethyltramadol (T:M1) ratios using phased and unphased genotype data from $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT aligned to the hg19/GRCh37 reference genome for varying feature selection stringencies compared to the observed toxicologically determined T:M1 using three supervised machine learning algorithms (1-nearest neighbor [1NN], linear regression [LR], and random forest [RF]). The shading of data points is scaled to represent the relative abundance of data points; dashed horizontal and vertical lines represent the average prediction accuracy due to random chance ( $5.59 ; 10 \%$-trimmed mean); solid diagonal lines represent the robust linear regression between the predicted and actual T:M1 with standard error represented by the grey shaded region surrounding each diagonal line.

Table S1. Amplicons Export file from Illumina TruSeq Custom Amplicon Design Studio. Each amplicon is given a unique identifier; amplicon information, including chromosome (Chr), start and stop positions relative to the hg19/GRCh37 reference genome, forward (F) or reverse (R) strand orientation, and total length, are listed; note that the "Avoid SNP" option was used for panel design.

| Amplicon |  | Start Coordinate | Stop Coordinate | Length | Strand | Amplicon |  | Start Coordinate | Stop Coordinate | Length | Strand | Amplicon |  | Start Coordinate | Stop Coordinate | ength | Strand |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 190848108 | 4 | 69962058 | 69962227 | 170 | R | 190848131 | 6 | 154428795 | 154428966 | 172 | F | 190848157 | 7 | 87183606 | 87183780 | 175 | R |
| 190848104 | 4 | 69962168 | 69962338 | 171 | F | 190848139 | 6 | 154428903 | 154429072 | 170 | R | 190848156 | 7 | 87183726 | 87183898 | 173 | F |
| 190848109 | 4 | 69962256 | 69962425 | 170 | R | 190848132 | 6 | 154429009 | 154429181 | 173 | F | 190848123 | 7 | 87183968 | 87184157 | 190 | R |
| 190848105 | 4 | 69962342 | 69962511 | 170 | F | 190848140 | 6 | 154429121 | 154429291 | 171 | R | 190848124 | 7 | 87189779 | 87189963 | 185 | R |
| 190848110 | 4 | 69962448 | 69962618 | 171 | R | 190848133 | 6 | 154429229 | 154429400 | 172 | F | 190848020 | 7 | 87190524 | 87190693 | 170 | R |
| 190848106 | 4 | 69962560 | 69962729 | 170 | F | 190848141 | 6 | 154429341 | 154429511 | 171 | R | 190848019 | 7 | 87190636 | 87190816 | 181 | F |
| 190848111 | 4 | 69962656 | 69962825 | 170 | R | 190848134 | 6 | 154429455 | 154429627 | 173 | F | 190848125 | 7 | 87191641 | 87191811 | 171 | R |
| 190848107 | 4 | 69962772 | 69962942 | 171 | F | 190848142 | 6 | 154429569 | 154429738 | 170 | R | 190848126 | 7 | 87194992 | 87195174 | 183 | R |
| 190848112 | 4 | 69962888 | 69963061 | 174 | R | 190848135 | 6 | 154429681 | 154429851 | 171 | F | 190848042 | 7 | 87195353 | 87195535 | 183 | R |
| 190848120 | 4 | 69963142 | 69963320 | 179 | R | 190848143 | 6 | 154429791 | 154429973 | 183 | R | 190848041 | 7 | 87195481 | 87195655 | 175 | F |
| 190848146 | 4 | 69964025 | 69964208 | 184 | R | 190848136 | 6 | 154429921 | 154430109 | 189 | F | 190848158 | 7 | 87195822 | 87195993 | 172 | R |
| 190848145 | 4 | 69964153 | 69964329 | 177 | F | 190848144 | 6 | 154430053 | 154430229 | 177 | R | 190848049 | 7 | 87196064 | 87196245 | 182 | R |
| 190848147 | 4 | 69964275 | 69964444 | 170 | R | 190848189 | 6 | 154431353 | 154431528 | 176 | R | 190848048 | 7 | 87196188 | 87196366 | 179 | F |
| 190848101 | 4 | 69968490 | 69968675 | 186 | R | 190848188 | 6 | 154431463 | 154431649 | 187 | F | 190848127 | 7 | 87196567 | 87196737 | 171 | R |
| 190848100 | 4 | 69968620 | 69968803 | 184 | F | 190848095 | 6 | 154439687 | 154439856 | 170 | R | 190848161 | 7 | 87199148 | 87199331 | 184 | R |
| 190848114 | 4 | 69972838 | 69973008 | 171 | R | 190848091 | 6 | 154439805 | 154439974 | 170 | F | 190848159 | 7 | 87199272 | 87199442 | 171 | F |
| 190848113 | 4 | 69972954 | 69973130 | 177 | F | 190848096 | 6 | 154439891 | 154440060 | 170 | R | 190848162 | 7 | 87199382 | 87199556 | 175 | R |
| 190848103 | 4 | 69973784 | 69973970 | 187 | R | 190848092 | 6 | 154439979 | 154440148 | 170 | F | 190848160 | 7 | 87199502 | 87199678 | 177 | F |
| 190848102 | 4 | 69973914 | 69974084 | 171 | F | 190848097 | 6 | 154440073 | 154440242 | 170 | R | 190848167 | 7 | 87214141 | 87214311 | 171 | R |
| 190848117 | 4 | 69978138 | 69978321 | 184 | R | 190848093 | 6 | 154440155 | 154440325 | 171 | F | 190848163 | 7 | 87214231 | 87214400 | 170 | F |
| 190848115 | 4 | 69978268 | 69978440 | 173 | F | 190848098 | 6 | 154440271 | 154440445 | 175 | R | 190848168 | 7 | 87214323 | 87214492 | 170 | R |
| 190848118 | 4 | 69978384 | 69978556 | 173 | R | 190848094 | 6 | 154440389 | 154440559 | 171 | F | 190848164 | 7 | 87214407 | 87214576 | 170 | F |
| 190848116 | 4 | 69978502 | 69978679 | 178 | F | 190848099 | 6 | 154440505 | 154440677 | 173 | R | 190848169 | 7 | 87214497 | 87214666 | 170 | R |
| 190848119 | 4 | 69978624 | 69978810 | 187 | R | 190848191 | 6 | 154567638 | 154567812 | 175 | R | 190848165 | 7 | 87214607 | 87214777 | 171 | F |
| 190847982 | 6 | 154331598 | 154331770 | 173 | R | 190848190 | 6 | 154567758 | 154567945 | 188 | F | 190848170 | 7 | 87214719 | 87214908 | 190 | R |
| 190847980 | 6 | 154331716 | 154331892 | 177 | F | 190848192 | 6 | 154567890 | 154568064 | 175 | R | 190848166 | 7 | 87214855 | 87215041 | 187 | F |
| 190847983 | 6 | 154331840 | 154332009 | 170 | R | 190848045 | 7 | 87133130 | 87133300 | 171 | R | 190848171 | 7 | 87214983 | 87215153 | 171 | R |
| 190847981 | 6 | 154331958 | 154332132 | 175 | F | 190848043 | 7 | 87133242 | 87133423 | 182 | F | 190848173 | 7 | 87224402 | 87224578 | 177 | R |
| 190847984 | 6 | 154332078 | 154332250 | 173 | R | 190848046 | 7 | 87133368 | 87133557 | 190 | R | 190848172 | 7 | 87224520 | 87224690 | 171 | F |
| 190847989 | 6 | 154360163 | 154360333 | 171 | R | 190848044 | 7 | 87133482 | 87133652 | 171 | F | 190848174 | 7 | 87224632 | 87224808 | 177 | R |
| 190847985 | 6 | 154360275 | 154360445 | 171 | E | 190848047 | 7 | 87133598 | 87133780 | 183 | R | 190848176 | 7 | 87224866 | 87225038 | 173 | R |
| 190847990 | 6 | 154360389 | 154360558 | 170 | R | 190848029 | 7 | 87135178 | 87135352 | 175 | R | 190848175 | 7 | 87224982 | 87225153 | 172 | F |
| 190847986 | 6 | 154360475 | 154360644 | 170 | F | 190848028 | 7 | 87135296 | 87135474 | 179 | F | 190848177 | 7 | 87225098 | 87225284 | 187 | R |
| 190847991 | 6 | 154360567 | 154360737 | 171 | R | 190848038 | 7 | 87138558 | 87138747 | 190 | R | 190848128 | 7 | 87225898 | 87226068 | 171 | R |
| 190847987 | 6 | 154360657 | 154360846 | 190 | F | 190848037 | 7 | 87138700 | 87138887 | 188 | F | 190848129 | 7 | 87228995 | 87229184 | 190 | R |
| 190847992 | 6 | 154360795 | 154360984 | 190 | R | 190848018 | 7 | 87144512 | 87144683 | 172 | R | 190848179 | 7 | 87229396 | 87229577 | 182 | R |
| 190847988 | 6 | 154360931 | 154361119 | 189 | F | 190848017 | 7 | 87144634 | 87144816 | 183 | F | 190848178 | 7 | 87229526 | 87229708 | 183 | F |
| 190848080 | 6 | 154407511 | 154407686 | 176 | R | 190848040 | 7 | 87145790 | 87145969 | 180 | R | 190848182 | 7 | 87229903 | 87230072 | 170 | R |
| 190848074 | 6 | 154407631 | 154407800 | 170 | F | 190848016 | 7 | 87148605 | 87148775 | 171 | R | 190848180 | 7 | 87230023 | 87230193 | 171 | F |
| 190848081 | 6 | 154407719 | 154407888 | 170 | R | 190848015 | 7 | 87148721 | 87148901 | 181 | F | 190848183 | 7 | 87230141 | 87230315 | 175 | R |
| 190848075 | 6 | 154407829 | 154407998 | 170 | F | 190848039 | 7 | 87150059 | 87150243 | 185 | R | 190848181 | 7 | 87230263 | 87230434 | 172 | F |
| 190848082 | 6 | 154407931 | 154408101 | 171 | R | 190848024 | 7 | 87160531 | 87160720 | 190 | R | 190848035 | 7 | 87342390 | 87342562 | 173 | R |
| 190848076 | 6 | 154408041 | 154408211 | 171 | F | 190848023 | 7 | 87160665 | 87160837 | 173 | F | 190848034 | 7 | 87342506 | 87342686 | 181 | F |
| 190848083 | 6 | 154408151 | 154408320 | 170 | R | 190848025 | 7 | 87160783 | 87160967 | 185 | R | 190848036 | 7 | 87342632 | 87342821 | 190 | R |
| 190848077 | 6 | 154408235 | 154408404 | 170 | F | 190848033 | 7 | 87165741 | 87165919 | 179 | R | 190848051 | 22 | 19929218 | 19929396 | 179 | R |
| 190848084 | 6 | 154408343 | 154408512 | 170 | R | 190848030 | 7 | 87168549 | 87168735 | 187 | R | 190848050 | 22 | 19929344 | 19929516 | 173 | F |
| 190848078 | 6 | 154408459 | 154408628 | 170 | F | 190848022 | 7 | 87170628 | 87170802 | 175 | R | 190848053 | 22 | 19938425 | 19938597 | 173 | R |
| 190848085 | 6 | 154408577 | 154408761 | 185 | R | 190848021 | 7 | 87170748 | 87170936 | 189 | F | 190848055 | 22 | 19939016 | 19939190 | 175 | R |
| 190848079 | 6 | 154408703 | 154408873 | 171 | F | 190848027 | 7 | 87173412 | 87173584 | 173 | R | 190848054 | 22 | 19939140 | 19939318 | 179 | F |
| 190848086 | 6 | 154408823 | 154409007 | 185 | R | 190848026 | 7 | 87173530 | 87173715 | 186 | F | 190848052 | 22 | 19948687 | 19948874 | 188 | R |
| 190848089 | 6 | 154410926 | 154411106 | 181 | R | 190848149 | 7 | 87174106 | 87174292 | 187 | R | 190848121 | 22 | 19949715 | 19949886 | 172 | R |
| 190848087 | 6 | 154411054 | 154411243 | 190 | F | 190848148 | 7 | 87174238 | 87174427 | 190 | F | 190847978 | 22 | 19950013 | 19950192 | 180 | R |
| 190848090 | 6 | 154411188 | 154411371 | 184 | R | 190848032 | 7 | 87175142 | 87175324 | 183 | R | 190847977 | 22 | 19950139 | 19950321 | 183 | F |
| 190848088 | 6 | 154411320 | 154411498 | 179 | F | 190848031 | 7 | 87175270 | 87175448 | 179 | F | 190847979 | 22 | 19950275 | 19950457 | 183 | R |
| 190847998 | 6 | 154411954 | 154412124 | 171 | R | 190848122 | 7 | 87175913 | 87176083 | 171 | R | 190848073 | 22 | 19951054 | 19951224 | 171 | R |
| 190847993 | 6 | 154412062 | 154412232 | 171 | F | 190848151 | 7 | 87178498 | 87178675 | 178 | R | 190848072 | 22 | 19951170 | 19951353 | 184 | F |
| 190847999 | 6 | 154412176 | 154412345 | 170 | R | 190848150 | 7 | 87178624 | 87178800 | 177 | F | 190848071 | 22 | 19951658 | 19951827 | 170 | R |
| 190847994 | 6 | 154412288 | 154412457 | 170 | F | 190848152 | 7 | 87178750 | 87178922 | 173 | R | 190848070 | 22 | 19951782 | 19951969 | 188 | F |
| 190848000 | 6 | 154412396 | 154412565 | 170 | R | 190848009 | 7 | 87179036 | 87179206 | 171 | R | 190848063 | 22 | 19955932 | 19956102 | 171 | R |
| 190847995 | 6 | 154412508 | 154412677 | 170 | F | 190848004 | 7 | 87179150 | 87179319 | 170 | F | 190848056 | 22 | 19956054 | 19956228 | 175 | F |
| 190848001 | 6 | 154412590 | 154412759 | 170 | R | 190848010 | 7 | 87179240 | 87179410 | 171 | R | 190848064 | 22 | 19956172 | 19956341 | 170 | R |
| 190847996 | 6 | 154412680 | 154412849 | 170 | F | 190848005 | 7 | 87179352 | 87179521 | 170 | F | 190848057 | 22 | 19956294 | 19956469 | 176 | F |
| 190848002 | 6 | 154412766 | 154412939 | 174 | R | 190848011 | 7 | 87179440 | 87179609 | 170 | R | 190848065 | 22 | 19956414 | 19956603 | 190 | R |
| 190847997 | 6 | 154412876 | 154413063 | 188 | F | 190848006 | 7 | 87179528 | 87179698 | 171 | F | 190848058 | 22 | 19956544 | 19956714 | 171 | F |
| 190848003 | 6 | 154413010 | 154413180 | 171 | R | 190848012 | 7 | 87179642 | 87179811 | 170 | R | 190848066 | 22 | 19956664 | 19956833 | 170 | R |
| 190848186 | 6 | 154414186 | 154414365 | 180 | R | 190848007 | 7 | 87179726 | 87179896 | 171 | F | 190848059 | 22 | 19956780 | 19956950 | 171 | F |
| 190848184 | 6 | 154414308 | 154414497 | 190 | F | 190848013 | 7 | 87179842 | 87180018 | 177 | R | 190848067 | 22 | 19956898 | 19957067 | 170 | R |
| 190848187 | 6 | 154414448 | 154414632 | 185 | R | 190848008 | 7 | 87179964 | 87180136 | 173 | F | 190848060 | 22 | 19956988 | 19957157 | 170 | F |
| 190848185 | 6 | 154414576 | 154414764 | 189 | F | 190848014 | 7 | 87180082 | 87180266 | 185 | R | 190848068 | 22 | 19957076 | 19957249 | 174 | R |
| 190848137 | 6 | 154428473 | 154428643 | 171 | R | 190848154 | 7 | 87183032 | 87183214 | 183 | R | 190848061 | 22 | 19957194 | 19957381 | 188 | F |
| 190848130 | 6 | 154428571 | 154428742 | 172 | F | 190848153 | 7 | 87183162 | 87183337 | 176 | F | 190848069 | 22 | 19957334 | 19957522 | 189 | R |
| 190848138 | 6 | 154428685 | 154428854 | 170 | R | 190848155 | 7 | 87183282 | 87183466 | 185 | R | 190848062 | 22 | 19957464 | 19957633 | 170 | F |

Table S2. TruSeq Custom Amplicon Low Input manifest file for probes designed to target the exonic regions of UGT2B7, ABCB1, OPRM1, and COMT. Table S 2 is available at the publisher's website: https://www.nature.com/ejhg/.

## PART 4

## CONCLUSIONS

# CHAPTER 7 

# A Genome-Wide Association Study of Tramadol Metabolism from Post-Mortem Samples 

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Frank R Wendt
Anna-Liina Rahinainen
Jonathan L King
Antti Sajantila Bruce Budowle


#### Abstract

Tramadol is commonly prescribed to relieve moderate-to-severe pain. Phase I tramadol metabolism depends on cytochrome p450 family 2 , subfamily D, polypeptide 6 (CYP2D6) to form O-desmethyltramadol (M1). CYP2D6 is an extensively studied pharmacogene, and clinically genetic variants may be used to infer patient metabolizer phenotype. However, drug ADME (absorption, distribution, metabolism, and excretion) depends on many functional and structural proteins in a pathway(s), not just a single protein. Though CYP2D6 function is well characterized, there is a paucity of data regarding whether trans-acting metabolic enzymes, if any, also may contribute to idiosyncratic phenotypes following drug exposure. A genome-wide association study was performed scanning ~2.6 million single nucleotide polymorphisms (SNPs) to identify loci associated with the rate of tramadol to M1 metabolism (M1:T). Five markers (rs79983226/kgp11274252, rs9384825, rs62435418/kgp10370907, rs72732317/kgp3743668 and rs184199168/exm1592932) were highly significantly associated with M1:T with the presence of the alternate allele resulting in decreased M1:T. Replication of these relationships was performed with targeted massively parallel sequencing and supported the relative trends observed in the genome-wide scan. These SNPs reside within five genes (RFPL4B/RNF211, KHDRBS3, HCN1, ICA1, and RGL4) previously implicated with adverse reactions. Analysis of toxicological meta-data accompanying each sample revealed a significant positive linear correlation between M1:T and sample polypharmacy, with M1:T increases in samples carrying the rs $79983226 / \mathrm{kgp} 11274252$ alternate allele. Taken together, these data indicate five candidate loci for potential clinical inferences/predictions of metabolizer phenotype following exposure


to tramadol and possibly other opiates and highlight sample polypharmacy as a possible diagnostic covariate in post-mortem genetic studies.

## Introduction

Tramadol is an opioid agonist, structurally and metabolically similar to codeine [1, 2], commonly prescribed to treat moderate to severe post-operative, dental, and/or musculoskeletal pain [1]. Typically administered orally as a racemic mixture of (+) and (-) tramadol, it is rapidly and almost completely absorbed and transported to the liver where it is converted to O-desmethyltramadol (M1) by the cytochrome p450 family 2 subfamily D, polypeptide 6 (CYP2D6). M1 is the most pharmacologically active metabolite of the parent drug, has significantly higher affinity for opioid receptors, and is a more potent analgesic [3, 4].

Genetic variants of CYP2D6 are routinely used to predict metabolizer phenotype (MP) of patients and have demonstrated value in autopsy-negative post-mortem investigations [5-8]. This gene has been extensively studied in many global, regional, and isolated populations [917]. These population genetic characterizations and predictive assessments of selected single nucleotide polymorphisms (SNPs) have enabled refinement of prescription doses. However, CYP2D6 is only part of the full ADME (absorption, distribution, metabolism, and excretion) process and therefore may inaccurately or incompletely predict metabolic state of some individuals $[18,19]$.

It has been demonstrated that a combined (i.e., multigene) and/or comprehensive (i.e., full-gene) approach to predicting MP may lead to more efficacious patient outcomes than a targeted monogenic approach [20-22]. Altar, et al. [20, 21] described a combinatorial predictive model for antidepressant response in the clinic and demonstrated increased patient outcomes over a single-gene model. It is reasonable to hypothesize that increased efficacy may be achieved with multigenic models of other drug response pathways. While tramadol is a
commonly prescribed opioid analgesic, which depends on the activity of CYP2D6, there is little understanding of which additional enzymes play a role in idiosyncratic responses following tramadol exposure and how polymorphisms in genes encoding trans-acting metabolism and/or response enzymes may associate or interact with those of CYP2D6.

Herein, an exploratory genome-wide association study was performed to identify additional, potentially predictive, biomarkers for inferring the rate of tramadol metabolism in Finns, a valuable medical genetic cohort. Correlations were made between genetic variations and the rate of tramadol to M1 metabolism (M1:T) in deceased Finns. Patient polypharmacy was explored as an additional covariate in post-mortem genetic testing. These results indicate potentially informative targets for refining clinical and post-mortem predictions of metabolic activity and thus patient responses to tramadol and/or ancillary data for inferring cause and/or manner of death in medico-legal investigations. They also demonstrate that, while difficult to control in such studies, patient polypharmacy may be another factor to consider when attempting to elucidate the complex genotype-environment-phenotype interactions that may impact cause and manner of death.

## Materials and Methods

## Subjects

Whole blood preserved on FTA® cards was obtained from a total of 37 deceased Finns (13 females and 24 males) between the ages of 13 and 91 (mean $52.3 \pm 19.0$ ) years of age with concentrations of tramadol and M1 in their blood and an associated autopsy-determined under the International Statistical Classification of Diseases (ICD) and Health Related Problems, 10th Revision code [23]. All subjects and associated toxicology data were collected according
to the ethical handling of human subject practices of the University of Helsinki. Anonymized DNA samples from each subject were transferred to University of North Texas Health Science Center (UNTHSC) and handled according to the UNTHSC Institutional Review Board Protocol Number 2016-051.

## DNA Extraction and Quantitation

DNA was extracted from FTA cards using the QIAamp® DNA Investigator Kit and quantitated using the Quantifiler ${ }^{\mathrm{TM}}$ Trio DNA Quantification Kit according to their respective manufacturers' recommendations [24, 25]

## Genome-Wide Genotyping and Image Acquisition

Genotyping was performed using the Illumina Infinium® ${ }^{\circledR}$ LCG Assay [26] and Infinium® Omni2.5Exome-8 v1.3 BeadChip according to the manufacturer’s recommended protocol. Template DNA input ranged from 200 ng to 1 ng genomic DNA. Image acquisition was performed on the Illumina HiScan ${ }^{\mathrm{TM}}$ System using the iScan Control Software.

## Image Processing and Statistical Considerations

BeadChip images (.idat files) were analyzed in GenomeStudio® Genotyping Module v2.0.2, following the manufacturer's recommended quality control procedures [27, 28] including a Genotype Call (GenCall) Score cutoff of 0.15. Clustering was performed using the manufacturer's cluster (InfiniumOmni2-5-8v1-3_A1_ClusterFile.egt) and hg19 manifest (InfiniumOmni2-5-8v1-3_A1.bpm) files [29, 30]. Sensitivity study data were analyzed as an independent GenomeStudio project, providing insight into downstream genome-wide
association study sample preparation and analysis. In general, GenomeStudio® output files were analyzed further using the ggplot2 package in RStudio ${ }^{\circledR}$ version 3.3.1 $[31,32]$ and Microsoft Excel®.

## System Sensitivity

The capability of the Infinium LCG assay to analyze input DNA quantities substantially less than the manufacturer's recommended 200 ng was tested. Three samples were prepared at eight input DNA quantities: 200, 150, 100, 50, 25, 10, 5, and 1 ng . Comparisons of sensitivity data among different input DNA preparations were processed under the assumption that the 200 ng preparations produced the highest quality data and the genotype calls were accurate and correct. Under this assumption, high quality SNP-array data were obtained down to 25 ng of input DNA, a minimum threshold used for association study sample inclusion. Additional information for evaluating SNP-array sensitivity can be found in the Supplemental Materials and Methods.

## Association Study Pre-Processing

Post-hoc power considerations indicated that a sample size of 37 was sufficient for detecting a relatively large effect size $(|\rho|=0.5)$ with a power of $0.927(\alpha=0.05$; two tails $)$. Pre-processing followed the recommendations described by Turner, et al. [33] using PLINK version 1.90beta4.6 [34, 35] and involved analysis of marker quality, sample quality, and potential batch effects. After pruning, 1,499,150 autosomal loci (total of 1,537,230 loci) and all individuals remained for subsequent association studies [33]. A comprehensive description of marker and sample pre-processing can be found in the Supplemental Materials and Methods.

This study aimed to identify loci associated with M1:T in Finns. Image data processing involved robust linear regression and Pearson correlation in RStudio ${ }^{\circledR}$ using all pre-processed loci and toxicology information. The resulting p-values were corrected using the BenjaminiHochberg post-hoc correction for false discovery [36]. Manhattan plots of all p-values were generated using the qqman library in RStudio ${ }^{\circledR}$ [37]. All significantly associated loci were analyzed for apparent genotype clustering abnormalities in the iScan Control Software v3.4.8 [38] and pairwise linkage disequilibria (LD). Self-reported healthy cohort population data for significantly associated loci were extracted from the 1000 Genomes Project using the University of California at Santa Cruz (UCSC) Table Browser [39, 40] and compared to tramadol-exposed Finns.

Gene-ontology (GO) terms were searched using the Protein ANalysis THrough Evolutionary Relationships (PANTHER ${ }^{\mathrm{TM}}$ ) Classification System Version 12.0 [41, 42]. PANTHER overrepresentation test (release 20170413) using client textbox input was used to evaluate over- or under-enrichment of "GO biological process complete" terms relative to the GO Ontology Homo sapiens database (release 2017-09-26).

## Targeted Massively Parallel Sequencing

Independent replication of genotype-phenotype associations was performed for an additional 99 deceased tramadol-exposed Finns using in-house designed primers for the highly significant SNPs (rs79983326F-ATGCCACCACATCAGGCTAT; rs79983326RATGCTGGACCACAGGATTTC; rs984825F-TAGCTGCCATCTTTCTTATCCTG; rs984825R-CACTGCTGAAACCTAATCACCTC; rs62435418FCATATCCCAAAGCTACACAAGTCA; rs62435418R-

TTTGTTCATTTTCCAAACTGCTTA; rs72732317F-ATTCTAGGTTATGGGCACAGC; rs72732317R-TGGTCATGATCTGTCCTCTCA; rs184199168FCTACTCCATCACCAGCACCAT; rs184199168R-ATTTCCTGATGGTCCTCCAAG. Multiplexed PCRs were performed using the Qiagen® Multiplex PCR Kit with 1 ng input DNA and the standard multiplex PCR recommendations. Temperature cycling on a Eppendorf Mastercycler pro S (Eppendorf, Hamburg, Germany) was programmed as follows: $95^{\circ} \mathrm{C}$ for 15 minutes, 42 cycles of $94^{\circ} \mathrm{C}$ for 30 seconds, $60^{\circ} \mathrm{C}$ for 90 seconds, and $57^{\circ} \mathrm{C}$ for 90 seconds, and $72^{\circ} \mathrm{C}$ for 10 minutes [43]. Note that all PCR primers in the multiplex had melting temperatures below $60^{\circ} \mathrm{C}$ so an annealing temperature of $57^{\circ} \mathrm{C}$ was used. PCR products were size-separated on the Agilent 2200 TapeStation using the D1000 screentape [44] and quantified using the Qubit® dsDNA Broad Range assay [45] on the Qubit 2.0 fluorometer. Qubit quantification values were used to normalize each sample to $0.2 \mathrm{ng} / \mu \mathrm{l}$, which was used as input for Nextera XT library preparation [46]. Massively parallel sequencing (MPS) was performed on the Illumina MiSeq ${ }^{\text {TM }}$ using the MiSeq Reagent Kit v2 (2 x 250 bp read length) chemistry and v3 ( $2 \times 300 \mathrm{bp}$ read length). The resulting .fastq files were locally aligned to the hg38 reference genome using Burrows-Wheeler Aligner (bwa) mem command and the Sequence Alignment/Map Tools (SAMtools) view, sort, and index commands [51-53] The resulting sorted batch alignment/map (.sorted.bam) files were standard input for the Genome Analysis Toolkit (GATK) [54].

## Results

## Genotype Phenotype Association

Samples prepared for this association study had average template DNA inputs of 103 $\pm 48.5 \mathrm{ng}$ with a range of 200 to 58.0 ng . The average concentration of tramadol and M1, and the average $\mathrm{M} 1: \mathrm{T}$ ratio, were $3.87 \mathrm{mg} / \mathrm{l} \pm 6.27,0.410 \mathrm{mg} / \mathrm{l} \pm 0.576$, and $0.183 \pm 0.171$, respectively. Pearson's correlation was used to determine associations between $\mathrm{M} 1: \mathrm{T}$ and the genotypes of $1,499,150$ autosomal loci. A total of 3,033 loci, none of which deviated from HWE expectations, across all 22 autosomes (representing 888 genes) were significantly correlated with the M1:T phenotype (padj < $3.34 \times 10-8$; Figure 1). $91.1 \%$ of the genes were associated with a GO term (Figure 2). After Bonferroni correction for multiple testing, three GO biological processes exhibited nearly two-fold enrichment relative to the GO database: (1) cell-cell adhesion (GO:0098609; 2.28 fold enrichment; $\mathrm{p}=0.0240$ ), (2) neuron development (GO:0048666; 1.93 fold enrichment; $\mathrm{p}=0.0214$ ), and (3) circulatory system development (GO:0072359; 1.89 fold enrichment; $\mathrm{p}=0.0283$ ).


Fig. 1 Manhattan plot of $-\log 10(p$-value) for correlation between 1,499,150 autosomal loci and the O-desmethyltramadol:tramadol ratio (M1:T). The dashed horizontal line indicates genome-wide significance after correction for multiple testing ( $\mathrm{p}=3.34 \times 10-8$ ); the locus with the lowest p-value on each chromosome is annotated with either an rs number or Illumina's 1000 Genomes Project (kgp) indicator [30].


Fig. 2 Summary of gene ontology (GO) terms associated with genes of suggestive significance with the M1:T phenotype. GO terms reported by PANTHER ${ }^{\text {TM }}$ Version 12.0 (released 2017-07-10) for 888 genes associated with 3,033 loci meeting the suggestive significance threshold for assiciation with the rate of conversion for tramadol to M1 relative to the Homo sapiens all genes database using the client text box input.

Five loci had p-values lower than the Benjamini-Hochberg corrected value (Table 1): rs79983226/kgp11274252 (r2 = 0.762; chromosome 5), rs9384825 (r2 = 0.615; chromosome 6), rs62435418/kgp10370907 (r2 = 0.615; chromosome 7), rs72732317/kgp3743668 (r2 = 0.749 ; chromosome 8 ), and rs184199168/exm1592932 ( $22=0.610$; chromosome 22 ). The average alternate allele frequencies in the deceased Finn cohort were $0.0143,0.0571,0.0286$, 0.0441, and 0.0286 for rs184199168/exm1592932, rs72732317/kgp3743668, rs62435418/kgp10370907, rs79983226/kgp11274252, and rs9384825, respectively. There were no significant differences in allele frequencies between the affected cohort and the 1000 Genomes Project FIN self-reported healthy population. Note that in a large cohort of mixed phenotype Finns housed in the Sequencing Initiative Suomi (SISu v4.1),
rs184199168/exm1592932 has a minor allele frequency of 0.00310 . Due to the exome-targeted nature of the project, the remaining four loci are not reported in SISu [47]. After Bonferroni correction ( $p_{\text {adj }}=0.00192$ ), significant pairwise LDs were observed for $8 / 10$ pairs. Additionally, the multi-locus (all five markers together) LD was significant ( $\mathrm{p}<0.00192$ ). These LDs may indicate some association at the SNP level, or in combination, with various features of these four samples (i.e., in this sampling of 74 chromosomes, a maximum of five haplotypes were observed with four of them occurring only once). According to their death certificates, these four individuals died as a result of poisoning by, adverse effect of, and underdosing of systemic antibiotics (ICD-T36; $\mathrm{N}=2$ ), closed fracture to vault of skull (ICD10S02.0; $\mathrm{N}=1$ ), and other specified chronic pulmonary disease (ICD10-J44.8; $\mathrm{N}=1$ ) [23]. It may also be postulated that this observation be attributed to allele dropout and/or the relatively small sample size and the presence of low frequency alleles/genotypes in the same four individuals (Table S1; samples 26, 27, 31, and 37). This situation may lead to a significant LD pattern by chance while a true interaction on the population level may not be significant. While the LDs observed in the test population are not significant in the 1000 Genomes Project FIN cohort [48], sensitivity data (Figure S2) demonstrate that there were no significant differences between allele dropout at 50 ng versus 200 ng input DNA.

Table 1 Summary of loci with strong significance to the O-desmethyltramadol:tramadol ratio in autopsied Finns. Omni2.5exome8 v1.3 locus names were cross referenced to their corresponding rs numbers and general locus information is provided, including chromosome (Chr), forward (F) or reverse (R) strand, reference genome positions and alleles (relative to the F strand), global minor allele frequency (gMAF), p-value for Pearson's r correlation, and relevant genes.

| Locus rs <br> Number | $\begin{gathered} \text { Omni2.5exome-8 } \\ \text { v1.3 Locus } \\ \hline \end{gathered}$ | Chr | Strand | Hg19 <br> Position | Hg38 <br> Position | Reference Allele | gMAF | p | Gene(s) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| rs79983226 | kgp11274252 | 5 | R | 45595655 | 45595553 | G | 0.0066 | $1.703 \times 10^{-11}$ | HCN1 |
| rs9384825 | rs9384825 | 6 | F | 112668193 | 112346991 | C | 0.1983 | $2.537 \times 10^{-8}$ | $\begin{gathered} \hline R F P L 4 B / R N F 2 \\ 11^{\mathrm{a}} \\ \hline \end{gathered}$ |
| rs62435418 | kgp10370907 | 7 | F | 8187646 | 8148016 | G | 0.0044 | $2.537 \times 10^{-8}$ | ICAI |
| rs72732317 | kgp3743668 | 8 | F | 136425579 | 135413336 | G | 0.0116 | $1.987 \times 10^{-11}$ | KHDRBS3 ${ }^{\text {a }}$ |
| rs184199168 | exm1592932 | 22 | F | 24034611 | 23692424 | T | 0.0002 | $3.043 \times 10^{-8}$ | GUSBP1 $1{ }^{\mathrm{b}}$ and RGL4 |

the five variants detected, these include: Sort Intolerant from Tolerant (SIFT) [49, 50, 52-54], Polymorphism Phenotyping v2 (PolyPhen-v2) [55, 56], Protein Variant Effect Analyzer (PROVEAN) [58, 61], Human Splicing Finder (HSF) [60], Regulome Database (RegulomeDB) [62], and Combined Annotation Dependent Depletion (CADD) [63]. One SNP, rs184199168/exm1592932, is a missense mutation at position 90 of ral guanine nucleotide association stimulator like 4 (RGL4), causing a leucine to glutamine amino acid change (CADD: 22.7; SIFT: 0.001; PROVEAN: -2.84; PolyPhen-v2: 0.999). Note that the CADD score for rs184199168/exm1592932 identifies it within the top $1 \%$ of damaging polymorphisms relative to all possible genomic substitutions. Two loci are found within the intronic regions of potassium/sodium hyperpolarization-activated cyclic nucleotide-gated channel 1 (HCN1; rs79983226/kgp11274252) and islet cell autoantigen 1 (ICA1; rs62435418/kgp10370907); however, these loci are located too far from an exon (> 1000 bases) to perform HSF splice site predictions. Using RegulomeDB, rs79983226/kgp11274252 (score: 6) and rs62435418/kgp10370907 (score: 3a) were scored as having minimal impact on gene regulation and likely to affect transcription factor binding (though expression quantitative trait locus observations have not been reported), respectively. Lastly, two loci are located just
upstream of exon 1 of Ret Finger Protein-like 4B (RFPL4B/RNF211; rs $9384825 / \mathrm{kgp} 10370907$ ) and KH domain-containing, RNA-binding, signal transductionassociated protein 3 (KHDRBS3; rs72732317/kgp3743668) and are not searchable in SIFT [49, 51-54, 57], PolyPhen-v2 [55-57], PROVEAN [58, 61], or HSF [60]. However, they are predicted to have little impact on protein function or regulation rs $9384825 / \mathrm{kgp} 10370907$ and rs72732317/kgp3743668, with CADD scores of 0.460 and 0.149 , respectively, and RegulomeDB scores of 6 and 5, respectively. In general, these five genes have been associated with epilepsy (including sudden unexpected death in epilepsy; HCN1 [64, 65]), asthma and allergic reactions, specifically in Europeans (RFPL4B [66, 67]), neurotransmitter transport (ICA1 [68-70]), expression of synapse function regulators in brain neuron populations (KHDRBS3 [71, 72]), and chemosensitivity in breast cancer treatment (RGL4 [73]), adding weight to their detection as tramadol ADME-relevant loci.

## Independent Replication

Although the sample size is small, these five SNPs were highly significantly associated with metabolism rate. Given the samples size, the empirically determined associations between these five loci and the M1:T phenotype were tested in two phases: first, genotype-M1:T relationships were identified in the 37 genome-wide association samples; second, the conclusions were assessed in an additional set of samples by targeted PCR and sequencing by MPS. The empirical associations between these five loci and the M1:T phenotype were tested using a Student's t-test (Figure 3 and Table S1). Note that to account for sample size, genotypes are analyzed in terms of homozygous reference versus alternate allele carriers. Generally, the presence of the alternate allele in all five loci was connected to a decreased conversion of
tramadol to its primary metabolite; however, the significance of these differences was only evaluated for rs9384825, rs62435418/kgp10370907, rs72732317/kgp3743668, and rs79983226/kgp11274252 due to multiple observations of the heterozygous genotype at each locus. For these loci, the heterozygous condition resulted in significantly decreased M1:T ratio ( $\mathrm{p}<0.05$ ). Though no mean M1:T ratio was present in this dataset for the rs184199168/exm1592932 heterozygous and homozygous-alternate genotypes (one observation of each), the trend of decreased M1:T ratio was observed but not statistically evaluated.


Fig. 3 Association between genotype at five genome-wide significant loci and the ratio of M1 to tramadol (T) for N = 37 (Omni2.5exome8 v1.3; "SNPchip"), $\mathrm{N}=99$ (NexteraXT; "MPS"), and $\mathrm{N}=136$ ("All") individuals. Each boxplot represents a single genotype relative to the forward DNA strand of the indicated single nucleotide polymorphism locus; the center horizontal line represents the median, the lower and upper boundaries of each box represent the first and third quartiles, respectively; the top and bottom vertical lines indicate plus and minus three times in the interquartile range, respectively; boxplot outliers are indicated by black data points. A student's $t$-test was used to compare the mean M1:T ratio ("M1T") between the homozygous-reference genotype at each locus and all other genotypes observed more than once with asterisks indicating $\mathrm{p}<0.05\left(^{* *}\right)$ and $0.1(*)$; "NA" indicates absence of genotype call. Note that the heterozygous "SNPchip" genotypes were observed in the same four individuals.

To further support the association output from PLINK, which uses independent genotypes (e.g., $\mathrm{AA}, \mathrm{AB}$, and BB ), individuals were pooled into groups of homozygous reference and alternate allele carriers for rs72732317/kgp3743668 ( $\mathrm{N}=3 / 37$ ) and rs79983226/kgp11274252 ( $\mathrm{N}=3 / 37$ ). Both loci exhibited significantly decreased $\mathrm{M} 1: \mathrm{T}$ in the presence of the alternate allele relative to the homozygous reference condition ( $\mathrm{p}=0.000202$ and 0.0278 for rs72732317/kgp3743668 and rs79983226/kgp11274252, respectively).

A pentaplex PCR and subsequent targeted MPS were used to independently replicate the genotype-phenotype associations observed in an additional 99 Finns plus the four rare SNP array haplotypes. The average read depth for each locus was 102X $\pm 40.4$ $(r s 79983226 / \mathrm{kgp} 11274252), \quad 113 \pm 45.9 \quad(\mathrm{rs} 9384825 / \mathrm{kgp} 10370907), \quad 93.5 \quad \pm 39.9$ (rs62435418/kgp10370907), 91.4X $\pm 38.8$ (rs72732317/kgp3743668), and $125 \pm 58.2$ (rs184199168/exm1592932). All four rare haplotypes detected with the SNP array data were concordant with the associated targeted sequencing data. Considering just the replicate population, there were no significant differences between pairwise comparisons of the homozygous reference, heterozygous, and homozygous alternate genotypes (Figure 3). To maximize the sample size for overall representation of tramadol to M1 conversion in Finns, all 136 samples were pooled. The alternate allele frequencies in this cohort were 0.0294 for rs79983226/kgp11274252, 0.0331 for rs9384825, 0.0184 for rs62435418/kgp10370907, 0.0478 for $\mathrm{rs} 72732317 / \mathrm{kgp} 3743668$, and 0.00368 for $\mathrm{rs} 184199168 / \mathrm{exm} 1592932$. As observed in the association study cohort, there are relatively decreased M1:T ratios for Finns carrying the alternate allele at rs62435418/kgp10370907 and rs9384825 but these relationships are not significant. The presence of the heterozygous condition at the SNPs rs79983226/kgp11274252 and rs72732317/kgp3743668 resulted in relatively decreased M1:T ratios (p < 0.1).

Interestingly, it appears that the homozygous alternate genotype at rs72732317/kgp3743668 may be associated with the reverse effect of that of the heterozygous condition while at rs79983226/kgp11274252 the heterozygous effect is exacerbated. In the total population of 136 Finns, there were no deviations from HWE after Bonferroni correction. The combined impact of all five loci on M1:T was investigated using multifactorial analysis of variants (ANOVA). There were significant relationships between rs79983226/kgp11274252 ( $\mathrm{p}=$ 0.00952 ) and the combination of rs9384825 and rs72732317/kgp3743668 ( $\mathrm{p}=0.00242$ ); however, specific pairwise genotype combinations were not significant (Tukey Honest Significant Difference test).

Interestingly, the LD structure observed with the SNP-array data only also was observed in the total dataset (padj < 0.002). Significant LD for the group of five loci may indicate real relationships rather than spurious observation of all five alternate alleles in the same individual(s) as the larger dataset includes greater distribution of allele combinations across individuals. Considering the dataset as a whole $(\mathrm{N}=136)$, there were no significant relationships between the five-locus haplotype and M1:T with or without inclusion of outliers (one-way ANOVA; $\mathrm{p}=0.966$ and 0.412 , respectively). Nevertheless, functional/mechanistic consequences of this LD need to be validated in controlled studies.

## Covariate Considerations

The samples analyzed above represent a non-random sampling of deceased individuals with an exhaustive list of additional compounds detected during routine autopsy toxicology screening. These data were explored in the context of the genotype-phenotype relationships described above. There were no detectable significant relationships between the M1:T and age,
sex, or specific compounds in the toxicology data; however, the combined impact of the number of additional compounds plus the rs79983226/kgp11274252 genotype plus the MoD significantly impacted M1:T (multiple linear regression; $\mathrm{p}=0.00673$ ). The number of additional compounds in a sample's toxicology screen was positively correlated with the M1:T ratio in the trauma MoD cohort (Pearson's $r=0.344 ; p=0.0258$; Figure 4) and the same relative observation is seen with the disease (Pearson's $r=0.0235$ ), suicide (Pearson's $r=$ 0.0159 ), and merged MoD (Pearson's $r=0.0900$ ) cohorts. Though the sample size is small, the slope of the linear regression describing the relationship between the number additional compounds and $\mathrm{M} 1: \mathrm{T}$ is significantly greater for the disease, suicides, and trauma MoDs carrying the alternate allele at rs79983226/kgp11274252 (p<0.05); however, the suicide cohort demonstrated an inverse relationship between the two variables. These observations suggest that M1:T is generally higher in individuals with more compounds in their blood.

The number of additional compounds detected in sample toxicology screens was evaluated for all alternate allele carriers (heterozygotes plus homozygous alternate samples) versus homozygous reference samples at each locus individually. The number of additional compounds detected was significantly greater in the rs72732317/kgp3743668 alternate allele carriers ( 6.8 compounds $\pm 3.66 ; \mathrm{N}=11$ ) relative to the homozygous reference samples (4.57 compounds $\pm 2.59 ;$ Student's $t$-test; $\mathrm{p}=0.0419$ ). While not significant, there was a general increase in the number of additional compounds in the blood of alternate allele carriers when all five loci of interest are pooled ( 5.56 compounds $\pm 3.19$ ) relative to those with the homozygous reference condition ( 4.95 compounds $\pm 3.36$ ).


Fig. 4 Robust linear regression between the number of additional compounds in each sample toxicology screen and the ratio of O-desmethyltramadol to tramadol for homozygous reference ("Ref") and alternate ("Alt") allele carriers at the rs79983226/kgp11274252 locus for disease, suicide, and trauma manners of death. Note that standard error is shown in grey surrounding each blue regression line.

These observations suggest that the M1:T values in Figure 3 possibly may be inflated compared to those in the absence of additional compounds, particularly for samples carrying an alternate allele at rs72732317/kgp3743668 and rs79983226/kgp11274252 and samples of the disease and trauma MoD classes ( $29.2 \%$ and $64.0 \%$ of the 25 total alternate allele carriers, respectively). The inflated M1:T measurements may have contributed to alternate allele carriers appearing more similar to the homozygous reference samples, leading to lack of
detection of significance between the mean M1:T at each genotype in the larger MPS and combined cohorts.

## Discussion

This study aimed to identify potential pharmacogenes associated with tramadol metabolism using genome-wide genotyping of a convenient cohort of deceased, tramadol-exposed Finns. 3,033 suggestive trait-associated loci were identified in the study group, five of which demonstrated genome-wide significance. In general, the presence of the alternate allele at rs9384825, rs62435418/kgp10370907, rs72732317/kgp3743668, and rs79983226/kgp11274252 correlated with decreased conversion of tramadol to its primary metabolite M1. Two genes identified here, ICA1 and HCN1, have been implicated in idiosyncratic drug reactions and death by potentiating hyperalgesia [68-70] and epilepsyassociated sudden unexpected death [64, 65], respectively. Two general themes of the five associated genes (RFPLAB/RNF211, KHDRBS3, HCN1, ICA1, and RGL4) are relatively high brain abundance and involvement in synaptic signal transduction. It may be reasonable to hypothesize that targeted assays involving a combination of liver (e.g. CYP2D6) and brain (e.g. HCN1) enzymatic variation may provide increased MP inferences and further improve patient efficacy. It should be noted that significant relationships between genotype and the M1:T phenotype were not detected when samples were pooled into a larger dataset. However, the number of additional compounds detected in the sample's toxicology screen (i.e. severity of patient polypharmacy) may significantly inflate the associated M1:T value, especially in trauma and disease MoDs. Though the sample size is relatively small, the alternate allele condition, most notably at rs72732317/kgp3743668 and rs79983226/kgp11274252, may
impact this observation, thereby contributing to lack of detection of significant genotypephenotype association in the combined dataset.

The data presented are limited by three main factors. (1) The sample size $(\mathrm{N}=136)$ may be relatively small for a study of this nature, decreasing the overall relative effect size that can be detected with confidence. An increased sample size may lead to identification of more rare loci, or loci with relatively small effects, that could contribute to the M1:T ratio [74]; however, the size of this quite unique cohort is not uncommon in genome-wide studies [75-77] and indeed, several targets of interest with relatively large effect sizes were detected. The Finnish population has a relatively small effect size and has been through at least one evolutionarily recent ancestral bottleneck, potentially enriching certain polymorphisms in the Finns which are rare in the general population and/or non-Finnish Europeans [78]. Conversely, certain globally common variants may not exist currently in the Finns; however, the sample size with which the general archive of variants can be detected is likely smaller than that of non-Finnish Europeans [79]. (2) The individuals used for this study were selected based on two criteria: a) died and had exposure to tramadol and b) sufficient DNA (between 50 and 200 ng ) for SNP array typing. Population substructure was not indicated by PCA and IBS testing; however, there may be inherent substructure in the cohort if considering MP selection based on CYP2D6 diplotype (i.e., the specific value of M1:T is associated with different CYP2D6 MP but was not considered an inclusion criterion for sample selection) [14, 80, 81]. The population used here represents a heterogeneous cohort of individuals who expired due to a variety of causes/manners of death. The data herein demonstrated that variation may exist in these categories individually that warrants their investigation as unique cohorts. Consequently, the associations identified here may need to be explored in larger studies focusing on CYP2D6
extreme MPs (poor and ultra-rapid) and/or MoD cohorts individually. Additionally, while typically considered relatively homogeneous, a fine level of east-west duality has been identified in the Finnish population $[82,83]$, which may need to be considered for subsampling individuals from these parts of the country. (3) Polypharmacy may be defined as the use of a) multiple, b) five or more, or c) multiple contraindicated drugs recreationally or to treat one or more medical conditions [86]. Multi-drug use, especially drugs which act as substrates for the same enzymes or enzymatic pathways, has the potential to confound association study results as the measured M1:T is contingent upon availability of CYP2D6 to metabolize tramadol. The presence of even minor non-tramadol CYP2D6 substrates may compete with tramadol for hepatic CYP2D6 binding sites, thereby artificially altering the M1:T phenotype, or any pharmacological measurement, being used to infer general MP. The deceased Finns in this study demonstrate polypharmacy as a confounding covariate for validating the genotypephenotype associations detected with the SNP-array data. Note that specific confounding compound/drug combinations were not discovered here, however the observed phenomenon is quite complex and will require additional controlled studies to fully elucidate the consequences of pairwise combinations of commonly co-administered drugs/medications.

The ancillary relationships identified here between sample degradation and inhibition and overall SNP array performance indicate that the relatively high recommended sample DNA input may not be a limiting factor for retrospective genome-wide interrogation of autopsied, blood-bank, and/or forensic-type samples, particularly those stored on FTA cards. Thus, large repositories of autopsy samples and data may be useful for comprehensive pharmacogenetic studies of phenotypes common to those individuals. These studies have the potential to provide meaningful insight into potential markers to target for clinical trials or clinical applications.

Additional targeted genotyping studies of the polymorphic nature of each gene reported here may be required to further explain specific SNP and/or gene interactions generating the M1:T phenotype. The BeadChip used in this study types primarily gene-associated loci. Cis- and/or trans-non-coding polymorphic sites may not be immediately informative but may demonstrate deleterious or advantageous effects in relation to phenotype of interest by altering splice junctions, regulating translational stability, and/or influencing gene promoter/enhancer sequences [84]. It is likely that through advances of continuous-read DNA sequencing and/or targeted genotyping assays, the functional relevance of these polymorphisms can be elucidated [85, 86].

## References

1. DePriest AZ, Puet BL, Holt AC, Roberts A, Cone EJ: Metabolism and Disposition of Prescription Opioids: A Review. Forensic Sci Rev 2015, 27:115-145.
2. Gong L, Stamer UM, Tzvetkov MV, Altman RB, Klein TE: PharmGKB summary: tramadol pathway. Pharmacogenet Genomics 2014, 24:374-380.
3. Gillen C, Haurand M, Kobelt DJ, Wnendt S: Affinity, potency and efficacy of tramadol and its metabolites at the cloned human mu-opioid receptor. Naunyn Schmiedebergs Arch Pharmacol 2000, 362:116-121.
4. Grond S, Sablotzki A: Clinical pharmacology of tramadol. Clin Pharmacokinet 2004, 43:879-923.
5. Kerr GW, McGuffie AC, Wilkie S: Tricyclic antidepressant overdose: a review. Emerg Med J 2001, 18:236-241.
6. Koren G, Cairns J, Chitayat D, Gaedigk A, Leeder SJ: Pharmacogenetics of morphine poisoning in a breastfed neonate of a codeine-prescribed mother. Lancet 2006, 368:704.
7. Koski A, Ojanpera I, Sistonen J, Vuori E, Sajantila A: A fatal doxepin poisoning associated with a defective CYP2D6 genotype. Am J Forensic Med Pathol 2007, 28:259-261.
8. Orliaguet G, Hamza J, Couloigner V, Denoyelle F, Loriot MA, Broly F, Garabedian EN: A case of respiratory depression in a child with ultrarapid CYP2D6 metabolism after tramadol. Pediatrics 2015, 135: $\mathrm{e} 753-755$.
9. Aklillu E, Persson I, Bertilsson L, Johansson I, Rodrigues F, Ingelman-Sundberg M: Frequent distribution of ultrarapid metabolizers of debrisoquine in an ethiopian population carrying duplicated and multiduplicated functional CYP2D6 alleles. J Pharmacol Exp Ther 1996, 278:441-446.
10. Bagheri A, Kamalidehghan B, Haghshenas M, Azadfar P, Akbari L, Sangtarash MH, Vejdandoust F, Ahmadipour F, Meng GY, Houshmand M: Prevalence of the CYP2D6*10 (C100T), *4 (G1846A), and *14 (G1758A) alleles among Iranians of different ethnicities. Drug Des Devel Ther 2015, 9:2627-2634.
11. Bernard S, Neville KA, Nguyen AT, Flockhart DA: Interethnic differences in genetic polymorphisms of CYP2D6 in the U.S. population: clinical implications. Oncologist 2006, 11:126-135.
12. Bradford LD: CYP2D6 allele frequency in European Caucasians, Asians, Africans and their descendants. Pharmacogenomics 2002, 3:229-243.
13. Contreras AV, Monge-Cazares T, Alfaro-Ruiz L, Hernandez-Morales S, Miranda-Ortiz H, Carrillo-Sanchez K, Jimenez-Sanchez G, Silva-Zolezzi I: Resequencing, haplotype construction and identification of novel variants of CYP2D6 in Mexican Mestizos. Pharmacogenomics 2011, 12:745-756.
14. Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS: Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med 2017, 19:69-76.
15. He X, He N, Ren L, Ouyang Y, Zhang N, Ma Y, Yuan D, Kang L, Jin T: Genetic polymorphisms analysis of CYP2D6 in the Uygur population. BMC Genomics 2016, 17:409.
16. Sistonen J, Fuselli S, Palo JU, Chauhan N, Padh H, Sajantila A: Pharmacogenetic variation at CYP2C9, CYP2C19, and CYP2D6 at global and microgeographic scales. Pharmacogenet Genomics 2009, 19:170-179.
17. Sistonen J, Sajantila A, Lao O, Corander J, Barbujani G, Fuselli S: CYP2D6 worldwide genetic variation shows high frequency of altered activity variants and no continental structure. Pharmacogenet Genomics 2007, 17:93-101.
18. Baber M, Chaudhry S, Kelly L, Ross C, Carleton B, Berger H, Koren G: The pharmacogenetics of codeine pain relief in the postpartum period. Pharmacogenomics J 2015, 15:430-435.
19. Lam J, Woodall KL, Solbeck P, Ross CJ, Carleton BC, Hayden MR, Koren G, Madadi P: Codeine-related deaths: The role of pharmacogenetics and drug interactions. Forensic Sci Int 2014, 239:50-56.
20. Altar CA, Carhart J, Allen JD, Hall-Flavin D, Winner J, Dechairo B: Clinical Utility of Combinatorial Pharmacogenomics-Guided Antidepressant Therapy: Evidence from Three Clinical Studies. Mol Neuropsychiatry 2015, 1:145-155.
21. Altar CA, Carhart JM, Allen JD, Hall-Flavin DK, Dechairo BM, Winner JG: Clinical validity: Combinatorial pharmacogenomics predicts antidepressant responses and healthcare utilizations better than single gene phenotypes. Pharmacogenomics J 2015, 15:443-451.
22. Wendt FR, Sajantila A, Moura-Neto RS, Woerner AE, Budowle B: Full-gene haplotypes refine CYP2D6 metabolizer phenotype inferences. Int J Legal Med 2017.
23. International Statistical Classification of Diseases and Health Related Problems, 10th Revision [http://www.icd10data.com/ICD10CM/Codes]
24. QIAamp ${ }^{\circledR}$ DNA Investigator Handbook June 2012 [https://www.qiagen.com/us/resources/resourcedetail?id=dcc5a995-3743-4219-914d94d6a28e49b3\&lang=en]
25. Quantifiler ${ }^{\text {TM }} \mathrm{HP}$ and Trio DNA Quantification Kits User Guide. Publication Number 4485354 Revision G [https://www.thermofisher.com/order/catalog/product/4482910]
26. Infinium® LCG Assay Protocol Guide. Part \# 15023139 Rev. D. June 2015 [https://support.illumina.com/content/dam/illuminasupport/documents/documentation/chemistry_documentation/infinium_assays/infinium_lcg_ assay/infinium-lcg-assay-guide-15023139-d.pdf]
27. Beeline Software 2.0 User Guide. Document \#1000000022181 v02. February 2017 [https://support.illumina.com/content/dam/illumina-support/documents/documentation/software_documentation/beeline/beeline-user-guide-1000000022181-02.pdf]
28. Infinium® Genotyping Data Analysis: A guide for analyzing Infinium genotyping data using the GenomeStudio ${ }^{\circledR}$ Genotyping Module [https://www.illumina.com/Documents/products/technotes/technote_infinium_genotyping_da ta_analysis.pdf]
29. Infinium Omni2.5-8 Kit Support [https://support.illumina.com/array/array_kits/humanomni2_58_beadchip_kit/downloads.html]
30. Infinium Omni2.5-8 v1.3 Support Files. Infinium Omni2.5Exome-8 v1.3 Loci Name to rsID Conversion File [https://support.illumina.com/downloads.html]
31. R: A language and environment for statistical computing. R Foundation for Statistical Computing. In R Core Team, 3.3.1 edition. New York: Springer-Verlag New Work.
32. Wickham H: ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York; 2009.
33. Turner S, Armstrong LL, Bradford Y, Carlson CS, Crawford DC, Crenshaw AT, de Andrade M, Doheny KF, Haines JL, Hayes G, et al: Quality control procedures for genomewide association studies. Curr Protoc Hum Genet 2011, Chapter 1:Unit1.19.
34. PLINK Version 1.90beta4.6.
35. Purcell S, Neale B, Todd-Brown K, Thomas L, Ferreira MA, Bender D, Maller J, Sklar P, de Bakker PI, Daly MJ, Sham PC: PLINK: a tool set for whole-genome association and population-based linkage analyses. Am J Hum Genet 2007, 81:559-575.
36. Hockberg YBaY: Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. Journal of the Royal Statistical Society Series B (Methodological) 1995, 57:289-300.
37. Turner S : qqman: an R package for visualizing GWAS results using $\mathrm{Q}-\mathrm{Q}$ and manhattan plots. 2014.
38. iScan Documentation and Literature [https://support.illumina.com/array/array_instruments/iscan/documentation.html]
39. Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, Korbel JO, Marchini JL, McCarthy S, McVean GA, Abecasis GR: A global reference for human genetic variation. Nature 2015, 526:68-74.
40. Karolchik D, Hinrichs AS, Kent WJ: The UCSC Genome Browser. Curr Protoc Bioinformatics 2012, Chapter 1:Unit1.4.
41. Mi H, Muruganujan A, Thomas PD: PANTHER in 2013: modeling the evolution of gene function, and other gene attributes, in the context of phylogenetic trees. Nucleic Acids Res 2013, 41:D377-386.
42. Thomas PD, Campbell MJ, Kejariwal A, Mi H, Karlak B, Daverman R, Diemer K, Muruganujan A, Narechania A: PANTHER: a library of protein families and subfamilies indexed by function. Genome Res 2003, 13:2129-2141.
43. Qiagen Multiplex PCR Handbook. For fast and efficient multiplex PCR without optimization. April 2010. [https://www.qiagen.com/us/resources/resourcedetail?id=beb1f99e-0580-42c5-85d4-ea5f37573c07\&lang=en]
44. Agilent D1000 ScreenTape System Quick Guide [https://www.agilent.com/cs/library/usermanuals/public/ScreenTape_D1000_QG.pdf]
45. Qubit® dsDNA BR Assay Kits. MAN0002325. MP32850. Revision A.0. [https://tools.thermofisher.com/content/sfs/manuals/Qubit_dsDNA_BR_Assay_UG.pdf]
46. Nextera XT DNA Library Prep Kit Reference Guide. Document \# 15031942 v02 [https://support.illumina.com/content/dam/illumina-support/documents/documentation/chemistry_documentation/samplepreps_nextera/nextera-xt/nextera-xt-library-prep-reference-guide-15031942-02.pdf]
47. [http://sisuproject.fi]
48. Pimenoff VN, Laval G, Comas D, Palo JU, Gut I, Cann H, Excoffier L, Sajantila A: Similarity in recombination rate and linkage disequilibrium at CYP2C and CYP2D cytochrome P450 gene regions among Europeans indicates signs of selection and no advantage of using tagSNPs in population isolates. Pharmacogenet Genomics 2012, 22:846-857.
49. Kumar P, Henikoff S, Ng PC: Predicting the effects of coding non-synonymous variants on protein function using the SIFT algorithm. Nat Protoc 2009, 4:1073-1081.
50. McLaren W, Gil L, Hunt SE, Riat HS, Ritchie GR, Thormann A, Flicek P, Cunningham F: The Ensembl Variant Effect Predictor. Genome Biol 2016, 17:122.
51. Ng PC, Henikoff S: Predicting deleterious amino acid substitutions. Genome Res 2001, 11:863-874.
52. $\quad \mathrm{Ng}$ PC, Henikoff S: Accounting for human polymorphisms predicted to affect protein function. Genome Res 2002, 12:436-446.
53. Ng PC, Henikoff S: SIFT: Predicting amino acid changes that affect protein function. Nucleic Acids Res 2003, 31:3812-3814.
54. Ng PC, Henikoff S: Predicting the effects of amino acid substitutions on protein function. Annu Rev Genomics Hum Genet 2006, 7:61-80.
55. Adzhubei I, Jordan DM, Sunyaev SR: Predicting functional effect of human missense mutations using PolyPhen-2. Curr Protoc Hum Genet 2013, Chapter 7:Unit7.20.
56. Adzhubei IA, Schmidt S, Peshkin L, Ramensky VE, Gerasimova A, Bork P, Kondrashov AS, Sunyaev SR: A method and server for predicting damaging missense mutations. Nat Methods 2010, 7:248-249.
57. McLaren W, Pritchard B, Rios D, Chen Y, Flicek P, Cunningham F: Deriving the consequences of genomic variants with the Ensembl API and SNP Effect Predictor. Bioinformatics 2010, 26:2069-2070.
58. Choi Y, Chan AP: PROVEAN web server: a tool to predict the functional effect of amino acid substitutions and indels. Bioinformatics 2015, 31:2745-2747.
59. Choi Y, Sims GE, Murphy S, Miller JR, Chan AP: Predicting the functional effect of amino acid substitutions and indels. PLoS One 2012, 7:e46688.
60. Desmet FO, Hamroun D, Lalande M, Collod-Beroud G, Claustres M, Beroud C: Human Splicing Finder: an online bioinformatics tool to predict splicing signals. Nucleic Acids Res 2009, 37:e67.
61. Choi M, Scholl UI, Ji W, Liu T, Tikhonova IR, Zumbo P, Nayir A, Bakkaloglu A, Ozen S, Sanjad S, et al: Genetic diagnosis by whole exome capture and massively parallel DNA sequencing. Proc Natl Acad Sci U S A 2009, 106:19096-19101.
62. Boyle AP, Hong EL, Hariharan M, Cheng Y, Schaub MA, Kasowski M, Karczewski KJ, Park J, Hitz BC, Weng S, et al: Annotation of functional variation in personal genomes using RegulomeDB. Genome Res 2012, 22:1790-1797.
63. Kircher M, Witten DM, Jain P, O'Roak BJ, Cooper GM, Shendure J: A general framework for estimating the relative pathogenicity of human genetic variants. Nat Genet 2014, 46:310-315.
64. Axler-Diperte G BF, Budimlija ZM, Sajantila A, Siegel D, and Tang Y: Molecular Autopsy. In Forensic DNA Applications: An Interdisciplinary Perspective. CRC Press; 2014: 453-482
65. Tu E, Waterhouse L, Duflou J, Bagnall RD, Semsarian C: Genetic analysis of hyperpolarization-activated cyclic nucleotide-gated cation channels in sudden unexpected death in epilepsy cases. Brain Pathol 2011, 21:692-698.
66. Ding L, Abebe T, Beyene J, Wilke RA, Goldberg A, Woo JG, Martin LJ, Rothenberg ME, Rao M, Hershey GK, et al: Rank-based genome-wide analysis reveals the association of ryanodine receptor-2 gene variants with childhood asthma among human populations. Hum Genomics 2013, 7:16.
67. Ortiz RA, Barnes KC: Genetics of allergic diseases. Immunol Allergy Clin North Am 2015, 35:19-44.
68. Cao M, Xu J, Shen C, Kam C, Huganir RL, Xia J: PICK1-ICA69 heteromeric BAR domain complex regulates synaptic targeting and surface expression of AMPA receptors. J Neurosci 2007, 27:12945-12956.
69. Li QJ, Wang Z, Yao YX, Jin SH, Qian MZ, Li NN, Wang YN, Zhang YW, Chen BY, Jia DY, et al: Loss of ICA69 potentiates long-lasting hyperalgesia after subcutaneous formalin injection into the mouse hindpaw. Neurochem Res 2015, 40:579-590.
70. Xu J, Kam C, Luo JH, Xia J: PICK1 mediates synaptic recruitment of AMPA receptors at neurexin-induced postsynaptic sites. J Neurosci 2014, 34:15415-15424.
71. Ehrmann I, Dalgliesh C, Liu Y, Danilenko M, Crosier M, Overman L, Arthur HM, Lindsay S, Clowry GJ, Venables JP, et al: The tissue-specific RNA binding protein T-STAR controls regional splicing patterns of neurexin pre-mRNAs in the brain. PLoS Genet 2013, 9:e1003474.
72. Traunmuller L, Gomez AM, Nguyen TM, Scheiffele P: Control of neuronal synapse specification by a highly dedicated alternative splicing program. Science 2016, 352:982-986.
73. Chang H, Jeung HC, Jung JJ, Kim TS, Rha SY, Chung HC: Identification of genes associated with chemosensitivity to SAHA/taxane combination treatment in taxane-resistant breast cancer cells. Breast Cancer Res Treat 2011, 125:55-63.
74. Korte A, Farlow A: The advantages and limitations of trait analysis with GWAS: a review. Plant Methods 2013, 9:29.
75. Behar DM, Yunusbayev B, Metspalu M, Metspalu E, Rosset S, Parik J, Rootsi S, Chaubey G, Kutuev I, Yudkovsky G, et al: The genome-wide structure of the Jewish people. Nature 2010, 466:238-242.
76. Pardo-Seco J, Gomez-Carballa A, Amigo J, Martinon-Torres F, Salas A: A genomewide study of modern-day Tuscans: revisiting Herodotus's theory on the origin of the Etruscans. PLoS One 2014, 9:e105920.
77. Salas A, Pardo-Seco J, Cebey-Lopez M, Gomez-Carballa A, Obando-Pacheco P, Rivero-Calle I, Curras-Tuala MJ, Amigo J, Gomez-Rial J, Martinon-Torres F: Whole Exome Sequencing reveals new candidate genes in host genomic susceptibility to Respiratory Syncytial Virus Disease. Sci Rep 2017, 7:15888.
78. Lim ET, Wurtz P, Havulinna AS, Palta P, Tukiainen T, Rehnstrom K, Esko T, Magi R, Inouye M, Lappalainen T, et al: Distribution and medical impact of loss-of-function variants in the Finnish founder population. PLoS Genet 2014, 10:e1004494.
79. Wang SR, Agarwala V, Flannick J, Chiang CW, Altshuler D, Hirschhorn JN: Simulation of Finnish population history, guided by empirical genetic data, to assess power of rare-variant tests in Finland. Am J Hum Genet 2014, 94:710-720.
80. Chen R, Wang H, Shi J, Shen K, Hu P: Cytochrome P450 2D6 genotype affects the pharmacokinetics of controlled-release paroxetine in healthy Chinese subjects: comparison of traditional phenotype and activity score systems. Eur J Clin Pharmacol 2015, 71:835-841.
81. Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS: The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther 2008, 83:234-242.
82. Hannelius U, Salmela E, Lappalainen T, Guillot G, Lindgren CM, von Dobeln U, Lahermo P, Kere J: Population substructure in Finland and Sweden revealed by the use of spatial coordinates and a small number of unlinked autosomal SNPs. BMC Genet 2008, 9:54.
83. Jakkula E, Rehnstrom K, Varilo T, Pietilainen OP, Paunio T, Pedersen NL, deFaire U, Jarvelin MR, Saharinen J, Freimer N, et al: The genome-wide patterns of variation expose significant substructure in a founder population. Am J Hum Genet 2008, 83:787-794.
84. Ward LD, Kellis M: Interpreting noncoding genetic variation in complex traits and human disease. Nat Biotechnol 2012, 30:1095-1106.
85. Ammar R, Paton TA, Torti D, Shlien A, Bader GD: Long read nanopore sequencing for detection of HLA and CYP2D6 variants and haplotypes. F1000Res 2015, 4:17.
86. Bank PC, Swen JJ, Guchelaar HJ, van der Straaten T: GenoChip CYP2D6 macroarray as a method to genotype for CYP2D6 variants: results of a validation study in a Caucasian population. Pharmacogenomics 2015, 16:681-687.

## Supplemental Information

## System Sensitivity

The capability of the Infinium LCG assay to analyze input DNA quantities substantially less than the manufacturer's recommended 200 ng was tested. Three samples were prepared at eight input DNA quantities: 200, 150, 100, 50, 25, 10, 5, and 1 ng . Comparisons of sensitivity data between different input DNA preparations were processed under the assumption that the 200 ng preparations produced the highest quality data and the genotype calls are accurate. Using this assumption, high quality SNP-array data were obtained down to 25 ng of input DNA. Samples included for association study testing had at

The assay contains four sample independent and four sample dependent controls housed on 15-30 beads of the BeadChip [1] which are used to evaluate workflow and betweensample performance, respectively. Sample-dependent and sample-independent controls performed as expected (Figure S1A). However, many of the metrics vary between BeadChips with the same preparation in a sample-independent manner and thus it was not possible to determine the limit of detection of the assay from these controls. Regardless, the mean sample call rate for all DNA template quantities was $>90 \%$, i.e., approximately 2.3 million out of 2.6 million loci typed at all input DNA quantities tested (Figure S1B). The overall quality of genotype calls decreased slightly as template DNA decreased. Considering the tenth (p10 GC) and fiftieth (p50 GC) percentile GenCall scores, respectively, the 200, 150, 100, 50, and 25 ng template preparations performed similarly with average p10 GC and p50 GC > 0.49 and 0.86 , respectively. The average call rates and p10 GC values for the 10,5 , and 1 ng preparations (call rates: $0.993 \pm 3.19 \times 10-3,0.989 \pm 4.43 \times 10-3$, and $0.913 \pm 4.40 \times 10-2$, respectively; p10 GC: $0.498 \pm 1.10 \times 10-3,0.497 \pm 1.56 \times 10-3$, and $0.443 \pm 3.51 \times 10-2$, respectively)
significantly deviated from those of the 200 ng preparations (call rate: $0.998 \pm 6.69 \times 10-4$; $\mathrm{p} 10 \mathrm{GC}: 0.500 \pm 2.11 \times 10-4 ; \mathrm{p}<0.04)$. This decrease in overall quality of genotype calls is correlated with an increased number of no call (NC) genotypes (Figure S1C); thus, the accuracy of some allele calls at individual loci may be impacted with lower amounts of template input.

Comparisons of sensitivity data between different input DNA preparations were processed under the assumption that the 200 ng preparations produced the highest quality data and the genotype calls are accurate. For comparisons to the 200 ng preparation the following operational definitions were used: locus dropout was any locus successfully typed in the 200 ng sample but assigned no call (NC) in a lower quantity sample; locus recovery was any locus assigned NC in the 200 ng sample but successfully typed in a lower quantity sample; allele dropout was any heterozygous locus in the 200 ng sample that was typed as a homozygous locus in a lower quantity sample; allele dropin was any homozygous locus in the 200 ng sample that was typed as a heterozygous locus in a lower quantity sample. Overall sample performance was quite high regardless of template DNA quantity; however, the decreased quality of genotype calls is more evident on the locus-level. Figure S2A shows the density distribution of p10 GC scores for eight template DNA quantities. The 200, 150, 100, 50, 25, 10, and 5 ng preparations show considerable overlap in distribution of the p10 GC scores while the 1 ng preparation had decreased abundance of high-quality loci, as demonstrated by the substantial decrease in density of p10 GC scores between 0.75 and 1.0. The p10 GC scores for the 200 ng preparations were compared to those of seven lower template DNA quantities in a pairwise manner (Figure S2B). When differences were observed, loci typically performed worse in the lower DNA quantity preparation; however, a relatively small set of loci performed better in

DNA template preparations less than the recommended 200 ng (data not shown). While interesting, this observation was nominal and may be attributed to stochastic sampling and/or unequal bead representation per locus per sample. In general, all sample preparations, with the exception of the 1 ng samples, the genotype calls for all template DNA preparations were similar to those of the 200 ng preparations even though genotype call scores decreased. The individual genotypes assigned to each locus also were compared to the genotype assigned to the 200 ng preparation (Figure S2C) using a $\chi 2$-goodness-of-fit test, considering each sample as a population of generic $\mathrm{AA}, \mathrm{AB}$, and BB genotypes representing homozygous allele 1 , heterozygous, and homozygous allele 2 genotypes, respectively. Significant differences were observed only with the genotype distributions of the 10,5 , and 1 ng preparations relative to the 200 ng preparations ( $\mathrm{p}<0.001$ ). While not significant, the three 25 ng preparations did have a prominently broad range of p -values relative to the 200 ng preparations, suggesting inconsistent performance with this template DNA quantity.

A key locus performance metric of interest is the loss of information at individual loci as a consequence of template DNA available for genome-wide amplification. Figure S2D compares the $150,100,50,25,10,5$, and 1 ng preparations to the 200 ng preparations to identify and characterize instances of locus dropout, locus recovery, allele dropout, and allele dropin as template DNA decreased. With the exception of locus recovery, there is an obvious relationship between DNA quantity and the occurrence of the remaining metrics. Locus and allele dropout (mean range of $1,140 \pm 119$ loci to $66,530 \pm 36,670$ loci and $64.7 \pm 7.64$ loci to $19,030 \pm 18,580$ loci for the 150 and 1 ng preparations, respectively) are tolerable and expected as template DNA decreases and stochastic effects during genome-wide amplification increase. Locus recovery and allele dropin (mean range of $1,230 \pm 322$ loci to $1,190 \pm 266$ loci and 70.3
$\pm 23.1$ loci to $41,770 \pm 20,950$ loci for the 150 and 1 ng preparations, respectively) may be the result of contamination and/or some cross hybridization, though not evident by the criterion of total heterozygosity across the loci in the samples tested (data not shown). It also should be noted that there may be very small levels of dropout and contamination on the locus and allele levels which may go undetected. Studies attempt to correct for these events during sample preprocessing by eliminating loci with a specified genotype call threshold and GC score but may not be readily apparent if the second allele of a heterozygote is consistently not typed.

## Association Study Pre-Processing

Marker quality assessments involved establishing appropriate genotype call rate and minor allele frequency (MAF) cutoffs, and evaluation of possible genotyping errors. All Xand Y-chromosomal and mitochondrial loci, and any autosomal locus with MAF $=0$ were removed from the HWE analysis procedure resulting in family-wise testing of 1,499,150 loci for deviations from HWE expectations. There were 2,579 significant deviations from HWE expectations after Bonferroni correction (padj < $3.34 \times 10-8$ ) and a Manhattan plot indicates little-to-no pattern or clustering of HWE deviating loci (Figure S4). This value is substantially less than that due to chance alone $(\sim 74,958)$ and thus these loci were not removed from the dataset.

Sample quality was checked at multiple levels, including biological sex prediction accuracy, cryptic sample relatedness, sample profile call rate, and population substructure. Principal component analysis (PCA; mean-centered and normalized) and identity-by-state (IBS; autosomal loci only) were used to detect population substructure [2]; outliers (individual samples) were identified based on a sample's z-score converted distance to its nearest three
neighbors [3]. Sample call rates and p10 GC scores reflect high quality sample performance (Figure S5) with average call rates and p10 GC scores of $0.999 \pm 0.00191$ and $0.738 \pm 0.0218$, respectively. Biological sex predictions from PLINK were compared to those contained within the autopsy information for each sample. One sample was recorded as female but was predicted as a male from the genetic data. The sample also was determined to be of male origin based on quantitative PCR assay (see methods; data not shown). Additionally, the genome-wide heterozygosity of the sample is lower than the cohort mean ( $0.695 \pm 0.00223$ ) suggesting that the sample is not a mixture. Based on these observations, this sample was treated as being derived from a male. The underlying pairwise cryptic relatedness of samples was tested using PLINK (Figure S5A). All 666 pairwise comparisons have high Z0 ( 0.958 to 1; the proportion of loci where sample pairs share zero alleles) and low Z1 values ( 0 to 0.0421 ; the proportion of loci where sample pairs share one allele), respectively, indicating no cryptic relationships among the individuals (i.e., first, second, third degree relatives were not detected). The presence of population substructure has the potential to alter underlying allele frequency data and may affect the false positive rate. One potential outlier was detected visually using PCA (Figure S5B). This sample had low performing p10 GC score (0.619) and call rate (0.988) relative to other samples; however, its pairwise IBS z-scores are within two standard deviations of the cohort mean so it would not be considered an outlier in this study. Quantile-quantile plots of the z-score-converted first, second, and third nearest neighbor distances for each sample also indicated a lack of detectable population substructure as each observed z-scoreconverted distance was relatively close to the expected (Figure S5C). After pruning, all 37 samples (13 females and 24 males) were used for the association study.

Samples were processed in three batches of three (sensitivity samples), four, and one BeadChips. Batch effects (i.e., genotype-phenotype associations confounded by samples being processed in batches) were explored by comparing the MAFs and average call rates within and between BeadChip batches. No significant differences were detected between pairwise comparisons of sample call rate, p10 GC score, or MAFs with batch- or BeadChip-specific attributes.

Though not conventional quality metrics or considerations for sample inclusion, the age and storage conditions of post-mortem samples (i.e., sample degradation index and inhibition [inferred by internal PCR control cycle threshold (IPC Ct) values]) were considered additional factors influencing sample performance [4]. The degradation index (Figure 3) was significantly associated with sample call rate $(p=3.30 \times 10-9 ; r=-0.814)$ and $p 10$ GC scores $(p=2.53 \times 10-10 ; r=-0.851)$ but IPC Ct was not $(p>0.05 ; r=0.129$ and 0.192 for sample call rate and p10 GC score, respectively). Rahikainen, et al. [4] showed that DNA can degrade in aged blood samples stored in FTA paper, which might suggest that such archived samples may not be ideal for genomic studies. However, herein there was no relationship between collection year (2002 through 2012) and sample DI, IPC Ct, call rate, or p10GC (data not shown). These results support that post-mortem blood samples stored on FTA paper can provide sufficient quality template DNA for large-scale genomic studies.

This study aimed to identify loci associated with M1:T in Finns. Image data processing involved robust linear regression and Pearson correlation in RStudio ${ }^{\circledR}$ using all pre-processed loci and toxicology information. The resulting p-values were corrected using the BenjaminiHochberg post-hoc correction for false discovery [5]. Manhattan plots of all p-values were generated using the "qqman" library in RStudio ${ }^{\circledR}$ [6]. All significantly associated loci were
analyzed for apparent genotype clustering abnormalities in the iScan Control Software v3.4.8 [7] and pairwise linkage disequilibria (LD). Self-reported healthy cohort population data for significantly associated loci were extracted from the 1000 Genomes Project using the University of California at Santa Cruz (UCSC) Table Browser [8, 9] and compared to tramadol-exposed Finns.

## Supplemental References

1. BeadArray Controls Reporter Software Guide. Document \# 1000000004009 v00. October 2015 [https://support.illumina.com/content/dam/illuminasupport/documents/documentation/chemistry_documentation/infinium_assays/infinium_hd_ methylation/beadarray-controls-reporter-user-guide-1000000004009-00.pdf]
2. Price AL, Patterson NJ, Plenge RM, Weinblatt ME, Shadick NA, Reich D: Principal components analysis corrects for stratification in genome-wide association studies. Nat Genet 2006, 38:904-909.
3. Tian C, Gregersen PK, Seldin MF: Accounting for ancestry: population substructure and genome-wide association studies. Hum Mol Genet 2008, 17:R143-150.
4. Rahikainen AL, Palo JU, de Leeuw W, Budowle B, Sajantila A: DNA quality and quantity from up to 16 years old post-mortem blood stored on FTA cards. Forensic Sci Int 2016, 261:148-153.
5. Hockberg YBaY: Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. Journal of the Royal Statistical Society Series B (Methodological) 1995, 57:289-300.
6. Turner S : qqman: an R package for visualizing GWAS results using $\mathrm{Q}-\mathrm{Q}$ and manhattan plots. 2014.
7. iScan Documentation and Literature [https://support.illumina.com/array/array_instruments/iscan/documentation.html]
8. Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, Korbel JO, Marchini JL, McCarthy S, McVean GA, Abecasis GR: A global reference for human genetic variation. Nature 2015, 526:68-74.
9. Karolchik D, Hinrichs AS, Kent WJ: The UCSC Genome Browser. Curr Protoc Bioinformatics 2012, Chapter 1:Unit1.4.
10. Infinium Omni2.5-8 v1.3 Support Files. Infinium Omni2.5Exome-8 v1.3 Loci Name to rsID Conversion File [https://support.illumina.com/downloads.html]

## Supplemental Figures



Fig. S1 Sample performance summary ( $\mathrm{N}=3$ individuals per template quantity [in nanograms]). A) Sample-dependent and sample-independent control signal intensities by template DNA quantity. B) Call rate versus genotype call (GenCall) score for each sample at each template DNA quantity. C) Sample profile composition at each DNA quantity using the generic abbreviations $\mathrm{AA}, \mathrm{AB}, \mathrm{BB}$, and NC for homozygous allele 1, heterozygous, homozygous allele 2, and no call genotypes, respectively


Fig. S2 Locus performance summary ( $\mathrm{N}=3$ individuals per template DNA quantity [in nanograms]) for approximately 2.6 million loci on the Infinuium Omni2.5Exome-8 v1.3 BeadChip. A) Density plot of the mean 10th percentile genotype call (GenCall) scores by template DNA in each sample preparation. It should be noted that there is considerable overlap between all DNA quantities except the 1 ng preparation. B) Density plot of the absolute value of the change $(|\Delta|)$ in 10th percentile GenCall Score distribution compared to a 200 ng sample. C) Chi-squared p-value distribution for genotype distributions using pairwise comparisons of the 200 ng sample with all other template DNA quantities. D) Distribution of locus dropout, locus recovery, allele dropout, and allele dropin counts for each template DNA quantity relative to the 200 ng sample profile. Locus dropout was defined as any locus successfully typed in the 200 ng sample but assigned no call (NC) in a lower quantity sample; locus recovery was defined as any locus assigned NC in the 200 ng sample but successfully typed in a lower quantity sample; allele dropout was defined as any heterozygous locus in the 200 ng sample that was successfully typed as a homozygous locus in a lower quantity sample; allele dropin was defined as any homozygous locus in the 200 ng sample that was successfully typed as a heterozygous locus in a lower quantity sample; power trend lines and R2 values are shown.


Fig. S3 Additional attributes influencing sample performance. Scatterplots, robust linear regression (solid lines), and $95 \%$ confidence intervals (shaded region) for the covariance of sample call rate and 10th percentile (p10) Genotype Call and DNA degradation index (DI) and internal PCR control cycle threshold (IPC Ct ) values (data not shown). Pearson's r-values indicated generally negative and positive relationships between the DI or IPC Ct values of the input DNA, respectively, and the sample call rate and p10 GenCall Scores, though only DI was significant $(\mathrm{p}=3.30 \times 10-9$ and $2.53 \times 10-10)$.


Fig. S4 Hardy-Weinberg Equilibrium p-values for 1,499,150 loci on chromosomes 1-22. The dashed horizontal lines indicate significance after Bonferroni correction ( $\mathrm{p}=3.34 \times 10-8$ ); the locus with the lowest p -value on each chromosome is annotated either with an rs number or Illumina's 1000 Genomes Project (kgp) indicator [10].


Fig. S5 Summary of sample pre-processing results. A) Scatterplot of identity-by-descent to determine cryptic relatedness within the sample cohort; Z 0 and Z 1 are the probabilities of pairwise sample comparisons sharing zero and one allele(s), respectively. B) Principal component (PC) analysis of 37 Finns using PC1 and PC2, identified using autosomal loci. The inset depicts the same information with the visual outlier removed. C) Quantile-quantile plot of the z -score-converted observed and theoretical distances between each sample and its first, second, and third nearest neighbors. The inset depicts the same information with the visual outlier from B removed.

## Supplemental Table

Table S1 Genotype data for five loci meeting genome-wide significance in relation to the ratio of O-desmethyltramadol to tramadol (M1:T) phenotype of 136 autopsied Finns. Genotypes are indicated in the forward strand; "NA" indicates missing genotype assignment; general sample information including biological sex, M1:T phenotype measurement, age, and genotyping method are provided.

| Sample Number | rs184199168/exm1592932 | rs72732317/kgp3743668 | rs62435418/kgp10370907 | rs79983226/kgp11274252 | rs9384825 | Sex | M1:T | Age | Method |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | TT | GG | GG | GG | CC | Male | 0.1875 | 28 | SNPchip |
| 2 | TT | GG | GG | GG | CC | Male | 0.25 | 68 | SNPchip |
| 3 | TT | GG | GG | GG | CC | Male | 0.161 | 47 | SNPchip |
| 4 | TT | GG | GG | GG | CC | Male | 0 | 55 | SNPchip |
| 5 | TT | GG | GG | GG | CC | Female | 0.25 | 91 | SNPchip |
| 6 | TT | GG | GG | GG | CC | Male | 0.0833 | 48 | SNPchip |
| 7 | TT | GG | GG | GG | CC | Female | 0.2 | 86 | SNPchip |
| 8 | TT | GG | GG | GG | CC | Female | 0.167 | 78 | SNPchip |
| 9 | TT | GG | GG | GG | CC | Male | 0.154 | 40 | SNPchip |
| 10 | TT | GG | GG | GG | CC | Male | 0.556 | 32 | SNPchip |
| 11 | TT | GG | GG | GG | CC | Male | 0.208 | 37 | SNPchip |
| 12 | TT | GG | GG | GG | CC | Male | 0.13 | 26 | SNPchip |
| 13 | TT | GG | GG | GG | CC | Male | 0 | 45 | SNPchip |
| 14 | TT | GG | GG | GG | CC | Female | 0.208 | 40 | SNPchip |
| 15 | TT | GG | GG | GG | CC | Male | 0.364 | 76 | SNPchip |
| 16 | TT | GG | GG | GG | CC | Female | 0 | 42 | SNPchip |
| 17 | TT | GG | GG | GG | CC | Female | 0.182 | 78 | SNPchip |
| 18 | TT | GG | GG | GG | CC | Female | 0.77 | 59 | SNPchip |
| 19 | TT | GG | GG | GG | CC | Male | 0.11 | 33 | SNPchip |
| 20 | TT | GG | GG | GG | CC | Male | 0 | 67 | SNPchip |
| 21 | TT | GG | GG | GG | CC | Male | 0.167 | 41 | SNPchip |
| 22 | TT | GG | GG | GG | CC | Male | 0.125 | 38 | SNPchip |
| 23 | TT | GG | GG | GG | CC | Female | 0.2 | 83 | SNPchip |
| 24 | TT | GG | GG | GG | CC | Male | 0.0882 | 44 | SNPchip |
| 25 | TT | GG | GG | GG | CC | Male | 0.5 | 68 | SNPchip |
| 26 | AT | TT | AG | CC | CT | Male | 0.0278 | 57 | SNPchip |
| 27 | TT | TG | AG | GC | CT | Male | 0.0556 | 39 | SNPchip |
| 28 | TT | GG | GG | GG | CC | Female | 0.111 | 63 | SNPchip |
| 29 | TT | GG | GG | GG | CC | Female* | 0.412 | 55 | SNPchip |
| 30 | TT | GG | GG | GG | CC | Male | 0.152 | 36 | SNPchip |
| 31 | TT | TG | GG | NA | CC | Male | 0.0741 | 78 | SNPchip |
| 32 | TT | GG | GG | GG | CC | Female | 0.333 | 13 | SNPchip |
| 33 | TT | GG | GG | GG | CC | Female | 0 | 39 | SNPchip |
| 34 | TT | GG | GG | GG | CC | Male | 0.171 | 33 | SNPchip |
| 35 | TT | GG | GG | GG | CC | Female | 0 | 66 | SNPchip |
| 36 | TT | GG | GG | GG | CC | Female | 0.255 | 60 | SNPchip |
| 37 | TT | GG | GG | GC | CC | Male | 0 | 28 | SNPchip |
| 38 | TT | GG | GG | GG | CC | Male | 0.10952 | 47 | MPS |
| 39 | TT | GG | GG | GG | CC | Male | 0.1579 | 57 | MPS |
| 40 | TT | GG | GG | GG | CC | Female | 0 | 52 | MPS |
| 41 | TT | GG | GG | GG | CC | Female | 0.1 | 89 | MPS |
| 42 | TT | GG | GG | GG | CT | Male | 0.40909 | 60 | MPS |
| 43 | TT | GG | GG | GG | CC | Male | 0.28571 | 38 | MPS |
| 44 | TT | GG | GG | GG | CC | Male | 0.14286 | 49 | MPS |
| 45 | TT | GG | GG | GG | CC | Female | 0.66667 | 69 | MPS |
| 46 | TT | GG | GG | GG | Ст | Female | 0.38 | 61 | MPS |
| 47 | TT | GG | GG | GG | CC | Male | 0.03421 | 33 | MPS |
| 48 | TT | GG | GG | GG | CC | Female | 0.14286 | 57 | MPS |
| 49 | TT | GG | GG | GC | CC | Female | 0.2 | 86 | MPS |
| 50 | TT | GG | GG | GG | CC | Female | 0.22222 | 59 | MPS |
| 51 | TT | GG | GG | GG | CC | Male | 0.16129 | 23 | MPS |
| 52 | TT | GG | GG | GG | CC | Female | 0.12727 | 66 | MPS |
| 53 | TT | GT | GG | GG | CC | Male | 0.06923 | 55 | MPS |
| 54 | TT | GG | GG | GG | CC | Male | 0.03333 | 17 | MPS |
| 55 | TT | GG | GG | GG | CC | Male | 0.14286 | 75 | MPS |
| 56 | TT | GG | GG | GG | CC | Male | 0.42857 | 65 | MPS |
| 57 | TT | GT | GG | GG | CT | Male | 0.18421 | 23 | MPS |
| 58 | TT | GG | GG | GG | CT | Female | 0.02619 | 67 | MPS |
| 59 | TT | GG | GG | GG | CC | Male | 0.03448 | 50 | MPS |
| 60 | TT | GG | GG | GG | CC | Female | 0.04546 | 49 | MPS |
| 61 | TT | GG | GG | GG | CC | Male | 0.152 | 55 | MPS |
| 62 | TT | GG | GG | GG | CC | Male | 0.09375 | 84 | MPS |
| 63 | TT | GG | GG | GG | CC | Male | 0.25 | 62 | MPS |
| 64 | TT | GG | GG | GG | CC | Male | 0.35714 | 28 | MPS |

Table S1 (continued) Genotype data for five loci meeting genome-wide significance in relation to the ratio of O-desmethyltramadol to tramadol (M1:T) phenotype of 136 autopsied Finns. Genotypes are indicated in the forward strand; "NA" indicates missing genotype assignment; general sample information including biological sex, M1:T phenotype measurement, age, and genotyping method are provided.

| Sample Number | rs184199168/exm1592932 | rs72732317/kgp3743668 | rs62435418/ kgp10370907 | rs79983226/kgp11274252 | rs9384825 | Sex | M1:T | Age | Method |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 65 | TT | GG | GG | GG | CC | Female | 0.11864 | 59 | MPS |
| 66 | TT | GG | GG | GG | CC | Male | 0.08333 | 31 | MPS |
| 67 | TT | GG | GG | GG | CC | Female | 0.13333 | 76 | MPS |
| 68 | TT | GG | GG | GC | CC | Male | 0.2037 | 21 | MPS |
| 69 | TT | GG | GG | GG | CC | Female | 0.12069 | 22 | MPS |
| 70 | TT | GG | GG | GG | CC | Female | 0.125 | 83 | MPS |
| 71 | TT | GG | GG | GG | CC | Female | 0.28571 | 63 | MPS |
| 72 | TT | GT | GG | GG | CC | Male | 0.18182 | 65 | MPS |
| 73 | TT | GG | GG | GG | CC | Male | 0.375 | 76 | MPS |
| 74 | TT | GG | GG | GG | CC | Male | 0.4 | 64 | MPS |
| 75 | TT | GG | GG | GG | CC | Female | 0.06667 | 65 | MPS |
| 76 | TT | GG | GG | GG | CC | Male | 0.17647 | 69 | MPS |
| 77 | TT | GG | GG | GG | CC | Male | 0.25 | 23 | MPS |
| 78 | TT | GG | GG | GG | CC | Male | 0.125 | NA | MPS |
| 79 | TT | GG | GG | GG | CC | Male | 0.14286 | 35 | MPS |
| 80 | TT | GG | GG | GG | CC | Female | 0.08889 | 89 | MPS |
| 81 | TT | GT | GG | GG | CC | Male | 0.04286 | 48 | MPS |
| 82 | TT | GG | GG | GG | CC | Male | 0.28571 | 69 | MPS |
| 83 | TT | GG | GG | GG | CC | Male | 0.28261 | 32 | MPS |
| 84 | TT | GG | GG | GG | CC | Male | 0.42857 | 54 | MPS |
| 85 | TT | GG | GG | GG | CC | Male | 0.2 | 42 | MPS |
| 86 | TT | GT | GG | GG | CC | Male | 0.18367 | 50 | MPS |
| 87 | TT | GG | GG | GG | CT | Male | 0.12 | 54 | MPS |
| 88 | TT | GG | GG | GG | CC | Male | 0.02326 | 41 | MPS |
| 89 | TT | GG | GG | GG | CC | Male | 0.21429 | 70 | MPS |
| 90 | TT | GG | GG | GG | CC | Male | 0.17143 | 77 | MPS |
| 91 | TT | GG | GG | GG | CT | Female | 0.08 | 86 | MPS |
| 92 | TT | GG | GG | GG | CC | Male | 0.07692 | 40 | MPS |
| 93 | TT | GG | AG | GG | CC | Male | 0.05882 | 46 | MPS |
| 94 | TT | GG | GG | GG | CC | Male | 0.27273 | 57 | MPS |
| 95 | TT | GT | GG | GG | CC | Female | 0.16667 | 21 | MPS |
| 96 | TT | GG | GG | GG | CC | Male | 0.05405 | 32 | MPS |
| 97 | TT | GG | GG | GG | CC | Female | 0.04 | 45 | MPS |
| 98 | TT | GG | GG | GG | CC | Male | 0.01429 | 56 | MPS |
| 99 | TT | GG | GG | GG | CC | Male | 0.25 | 63 | MPS |
| 100 | TT | GG | GG | GG | CC | Male | 0.18182 | 61 | MPS |
| 101 | TT | TT | GG | GG | CC | Male | 0.4 | 89 | MPS |
| 102 | TT | GG | GG | GG | CC | Male | 0.4 | 26 | MPS |
| 103 | TT | GG | GG | GG | CC | Female | 0.05556 | 46 | MPS |
| 104 | TT | GG | GG | GG | CC | Female | 0.17647 | 64 | MPS |
| 105 | TT | GG | GG | GG | CC | Male | 0.14286 | 55 | MPS |
| 106 | TT | GG | GG | GG | CC | Male | 0.28571 | 39 | MPS |
| 107 | TT | GG | GG | GG | CC | Female | 0.07813 | 62 | MPS |
| 108 | TT | GG | GG | GG | CC | Female | 0.07692 | 82 | MPS |
| 109 | TT | GG | GG | GG | CC | Female | 0.08462 | 36 | MPS |
| 110 | TT | GG | GG | GG | CC | Male | 0.4 | 70 | MPS |
| 111 | TT | GG | AG | GG | CC | Male | 0.25 | 94 | MPS |
| 112 | TT | GG | GG | GC | CC | Female | 0.08889 | 81 | MPS |
| 113 | TT | GG | AG | GG | CC | Female | 0.18182 | 54 | MPS |
| 114 | TT | GG | GG | GG | CC | Female | 0.125 | 92 | MPS |
| 115 | TT | GG | GG | GG | CC | Male | 0.21053 | 30 | MPS |
| 116 | TT | GG | GG | GG | CC | Male | 0.33333 | 57 | MPS |
| 117 | TT | GG | GG | GG | CC | Female | 0.16154 | 70 | MPS |
| 118 | TT | GG | GG | GG | CC | Male | 0.05517 | 55 | MPS |
| 119 | TT | GG | GG | GG | CC | Female | 0.07143 | 47 | MPS |
| 120 | TT | GG | GG | GG | CC | Female | 0.17647 | 67 | MPS |
| 121 | TT | GG | GG | GG | CC | Female | 0.09091 | 49 | MPS |
| 122 | TT | GG | GG | GG | CC | Male | 0.19355 | 50 | MPS |
| 123 | TT | GG | GG | GG | CC | Male | 0.18 | 52 | MPS |
| 124 | TT | GG | GG | GG | CC | Male | 0.36145 | 29 | MPS |
| 125 | TT | GG | GG | GG | CC | Male | 0.06667 | 31 | MPS |
| 126 | TT | GG | GG | GG | CC | Male | 0.20833 | 68 | MPS |
| 127 | TT | GT | GG | GG | CC | Male | 0.22222 | 66 | MPS |
| 128 | TT | GG | GG | GC | CC | Female | 0.15385 | 63 | MPS |
| 129 | TT | GG | GG | GG | CC | Male | 0.11111 | 82 | MPS |
| 130 | TT | GG | GG | GG | CC | Male | 0.15385 | 43 | MPS |
| 131 | TT | GG | GG | GG | CT | Male | 0.28571 | 89 | MPS |

Table S1 (continued) Genotype data for five loci meeting genome-wide significance in relation to the ratio of O-desmethyltramadol to tramadol (M1:T) phenotype of 136 autopsied Finns. Genotypes are indicated in the forward strand; "NA" indicates missing genotype assignment; general sample information including biological sex, M1:T phenotype measurement, age, and genotyping method are provided.

| Sample Number | rs184199168/ exm1592932 | rs72732317/kgp3743668 | rs62435418/ kgp10370907 | rs79983226/ kgp11274252 | rs9384825 | Sex | M1: ${ }^{\text {T }}$ | Age | Method |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 132 | TT | GG | GG | GG | CC | Female | 0.36364 | 33 | MPS |
| 133 | TT | GG | GG | GG | CC | Male | 0.12 | 22 | MPS |
| 134 | TT | GG | GG | GG | CC | Male | 0.5 | 71 | MPS |
| 135 | TT | GG | GG | GG | CC | Female | 0.5 | 62 | MPS |
| 136 | TT | GG | GG | GG | CC | Male | 0.2 | 40 | MPS |

## Chapter 8

Concluding Remarks on the Future Direction and Application of Comprehensive Pharmacogenetic Data

## Summary

This dissertation evaluated a comprehensive (full-gene) and combinatorial (multiple genes) predictive model of tramadol MP using information from five key pharmacogenes (CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT) under the hypothesis that comprehensive (full-gene) and combinatorial (multi-gene) pharmacogenetic profiles of select genes in the opiate metabolism and response pathways can be used to better predict MP of an individual. The overall strategy and approach to address this hypothesis involved two specific aims: (1) define a comprehensive list of opiate-metabolism-gene polymorphisms in unexposed populations and/or populations of exposed indivudlas with no adverse side effects and (2) evaluate the predictive capability of polymorphisms on deceased tramadol-exposed Finns.

In Specific Aim 1, three levels of analysis were performed using the publicly available 1000 Genomes Project self-reported healthy individuals: (1) assess global genetic diversity of opiate metabolism genes in healthy cohorts, (2) define CYP2D6 full-gene * alleles/haplotypes, and (3) perform haplotype analyses of $U G T 2 B 7, A B C B 1, O P R M 1$, and $C O M T$. This Aim was divided into three chapters (Chapter 2 through 4) addressing genetic diversity in self-reported healthy individuals. Chapter 2 characterized the population genetic diversity of approximately 15,000 single nucleotide polymorphisms (SNPs) and insertion/deletion polymorphisms (INDELs) within five genes involved in the opiate ADME (absorption, distribution, metabolism, excretion) and response processes and identified some degree of association between individual markers within different genes. Chapter $\mathbf{3}$ used data from Chapter 2 to characterize numerous polymorphisms in the CYP2D6 region that are not currently considered for * allele definitions. When included, the average CYP2D6 activity score decreased significantly, indicating that the inclusion of these loci is likely critical for clinical
implementation of CYP2D6 data. Additionally, the haplotype diversity of CYP2D6 is likely substantially higher than what is reported with existing targeted genotype approaches. Finally, Chapter 4 established full-gene haplotypes of $U G T 2 B 7, A B C B 1, O P R M 1$, and $C O M T$ and identified associations between the predicted activity of these trans-acting ADME and response proteins and the CYP2D6-predicted activity score.

Specific Aim 2 elaborated on the studies performed in Aim 1. This aim involved the design and empirical evaluation of a pathway-driven predictive model of MP in three phases. (1) Chapter 5 analyzed the full gene region of CYP2D6 and demonstrated the ability to predict normal versus non-normal MP with relatively high accuracy using supervised machine learning. These data demonstrated that CYP2D6 is generally sufficient for differentiating EM/NM from all other phenotypes with high accuracy. Using phased genotype data, however, offered only slightly increased prediction accuracy for those samples in the non-EM/NM categories (i.e. PM, IM, and UM). Ultimately, the heritability of T:M1 was quite low, suggesting that the full variation in phenotype is yet to be explained, or is not fully explained, by CYP2D6 information. (2) Chapter 6 utilized supervised machine learning and combinatorial genetic data from UGT2B7, ABCB1, OPRM1, and COMT to predict MP in the same cohort of tramadol-exposed Finns. This phase identified a subset of fourteen loci significantly associated with the T:M1 phenotype and identified $U G T 2 B 7$ as a pharmacogene maximally explaining phenotypic variance. (3) Chapter 6 also evaluated a fully combinatorial model (i.e., CYP2D6, UGT2B7, ABCB1, OPRM1, and COMT together) of tramadol metabolism. Using all five genes together produced significantly higher MP classification accuracies than the models using CYP2D6 alone. Overall, these data shed light on the association between various opiate ADME-R gene polymorphisms and the conversion of
tramadol to its primary metabolite M1. Additionally, associations between specific polymorphisms in all five target genes were observed. The combinatorial, pathway-driven model far exceeded the accuracy of the monogenic approach, and accuracy was maintained after an over 300 -fold reduction in loci required to make the prediction. Taken together, this finding demonstrated support of a comprehensive and combinatorial multigenic approach to tramadol pharmacogenetics.

To conclude this dissertation, in Chapter 7 the results of a genome-wide association study are described that identify potential additional genetic targets that may be relevant for future optimization of a combinatorial/pathway-driven approach to tramadol (and likely other opioids) pharmacogenetics of ante- and/or post-mortem patients. These data elucidated kgp11274252/rs79983226 (HCN1), rs9384825 (RFPL4B/RNF211), kgp10370907/rs62435418 (ICA1/ICA69/ICAp69), kgp3743668/rs72732317 (KHDRBS3/TSTAR/SLM2/SALP), and exm1592932/rs184199168 (RGL4) as potential genes to include in future studies due to their significant association with the rate of T to M1 conversion. Further analysis of the meta-data accompanying each sample identified patient polypharmacy as a significant confounding variable contributing to the T:M1 measurement in post-mortem tramadol-exposed Finns.

## Limitations

The presented dissertation is limited by four factors. First is the selection of the 1000 Genomes Project database as a starting point to investigate the five selected genes offers some bias in the loci that could reasonably be observed. While freely available and user-friendly, the read depth requirement for submission of sequence information to the 1000 Genomes Project
is quite low (~4X) (1000 Genomes Project Consortium, et al. 2015). Read depth this low produces an inherent level of error and/or allele drop out possibly resulting in missing data. Additionally, the relatively large sample size of the whole database $(\mathrm{N}=2,504)$ is divided into 26 smaller populations of approximately 100 individuals each. Combined with the selfreported healthy status of each sample, these features mean that some rare causal alleles will not be captured in the sample (1000 Genomes Project Consortium, et al. 2015). Finally, tests for departures from HWE and pairwise LD are sensitive to rare alleles as the homozygousalternate condition is presumably infrequent in healthy/unexposed populations (Teo, et al. 2007). A phenotype-positive population (i.e., drug-exposed) may select for individuals of the homozygous-alternate condition via sampling bias. While likely altering HWE of the population, this is a critical feature of identifying many causal loci by enriching for the causal variant(s) via selective sampling. Additionally, the 1000 Genomes Project is limited by sequence read depth. The low read depth of the 1000 Genomes Project (minimum of 4X) may inflate the pseudohomozygote frequency (i.e., heterozygotes that appear homozygous due to drop-out of one allele). As evidenced by the data generated to date in Phase 1 of Specific Aim 1, a large number of polymorphisms in the five selected genes are observed once in various super-populations. While possibly the result of population substructure, sampling variance, and/or natural selection of an allele in those populations, rare variants observed in the homozygous-alternate condition may skew the presented HWE and pairwise LD results and downstream application of these data to population pharmacogenetics.

The second limitation to this body of research is use of the Finnish population for Specific Aim 2. While valuable for medical genetic studies due to at least one relatively recent bottleneck event and resulting population homogeneity (Palo, et al. 2009), the population has
a relatively small effect size, meaning that certain causal polymorphisms will not be identified that may be quite frequent in the global population. However, the data obtained from using this population will serve as the first assessment of all five selected genes in the same homogeneous population, enabling characterization of common variants, stable genetic regions, and highly evolving regions and identify loci of importance for common disease/phenotypes with relatively diverse genetic etiologies. While the assumption of population homogeneity is typically made for medical genetic studies based on this population, there is real substructure effects between the eastern and western sides of the country (Hannelius, et al. 2008; Palo, et al. 2009). Though still lower relative to other populations, the degree of substructure is significant and may impact underlying genotype-phenotype associations depending on the specific geographic origin of samples collected for this dissertation and indeed future studies of the Finnish population.

Next, this dissertation used gene-targeted MPS of critical regions and computationally inferred genotype phase (the assignment of alleles to the paternal and maternal chromosomes). As described in Chapter 1, computational phase is a limiting factor for application of pharmacogenes, specifically CYP2D6, due to potentially inaccurate prediction of certain * alleles. The presented data somewhat overcome this limitation by using overlapping amplicons where appropriate (i.e., within an exon) in an effort to identify which polymorphic state can be assigned to each parental chromosome. While using phased * allele information is routine in the scientific community, the data from this dissertation demonstrate that phasing may not be necessary in routine diagnostic applications of the data, especially due to the poor amplification and interrogation of the Alu regions upstream of CYP2D6. It may be sufficient to type and identify the presence of only those polymorphisms with potential damaging consequences or
those showing maximal impact on the phenotype of interest, such as those described in Chapters 5 and 6 of this dissertation.

Lastly, the potential for drug-drug, drug-protein, and/or protein-protein interactions is a confounding factor in Specific Aim 2 (see Chapter 7). However, it is possible, and has been eluded to herein, that drugs in the toxicology reports of this Finnish population set have uncharacterized relationships with one or more of the five proteins of interest or other transacting opiate ADME and response proteins that confound these toxicological data and downstream association with genetic data. It may also be possible that there are protein-protein interactions unique to either extreme of the MP spectrum. These possibilities require additional controlled experiments to systemically assess the impact of specific drug combinations on the ability to predict MP using genetic information.

## Topic-specific Future Directions

A combinatorial, pathway-driven predictive model of ADME and response was generated to predict MP in a deceased tramadol-exposed Finnish population sample. The classifier accuracy relative to the CYP2D6-inferred MP is quite high (up to $96 \%$ depending on MP and classifier used); however, the features underlying the model rely on presence/absence of certain loci that may or may not be present in non-Finnish Europeans, other global/isolated populations, or individuals with a specific disease phenotype. Because of this populationspecific allele frequency variation, the features used for Finns may be different than those necessary to classify individuals from the Brazilian, Ashkenazi Jewish, or current cosmopolitan populations, for example. Studies have demonstrated that genotype-phenotype findings from a Finnish cohort are likely more applicable to other populations than those made
from non-Finnish Europeans, for example. The Finns have at least one relatively recent evolutionary bottleneck resulting in increased genetic homogeneity and potential enrichment of globally rare loci. Studies involving the applicability of Finnish population data to other populations are still required to identify relevant markers tha may be population specific and make the defined marker set relevant to a broad community. Additionally, the selected genes are key components of the tramadol ADME and response pathways but other opioid analgesics may not rely solely on these proteins of interest for their primary activation. Oxycodone, for example, is not an agonist of the OPRM1 receptor so the associated gene may not be appropriate for predicting phenotype following exposure to oxycodone using the model developed in this dissertation. Feasibility testing in groups exposed to different types of opiatebased medications would provide classifier accuracy and better describe the potential broad impact of this panel.

As listed above and overcome in Chapters 5 and 6, phasing of genotype data only is only as good as the bioinformatic pipeline and reference population(s) used to infer chromosomal association of SNPs. There are instruments available, such as nanopore technologies, to enable sequencing of single-stranded DNA and RNA of notable length (Feng, et al. 2015). The resulting data contain polymorphisms on the same read, eliminating ambiguity from computational phasing. Such devices are readily available for testing. Unfortunately, they are largely still in development stages with large error rates, and small alterations to their chemistry may have impeded the studies described herein or impacted the feasibility of study findings. The base calling accuracies and quality scores have improved but remain too low (approximately 67.4-85\%) for the interests of this project (Jain, et al. 2016; Jain, et al. 2016; Lindberg, et al. 2016; Lu, et al. 2016). As these chemistries become more
robust, utilizing the single molecule approaches may be vastly beneficial for combinatorial pharmacogenomic screening, especially for CYP2D6, which already aims to employ a more comprehensive genotyping strategy.

The word "comprehensive" has been used loosely throughout the presentation of these data to describe inclusion of CYP2D6 intron, exon, $5^{\prime}$ and $3^{\prime}$ untranslated regions, and promoter targets in the MP prediction. While substantially increasing the genetic data included in the tramadol MP prediction, there are a variety of additional regulatory elements and/or alternative gene selections that may or may not directly contribute to ADME and response for the broad opiate drug class or specific drugs in this class, such as tramadol. Wang, et al. (2014) characterized two polymorphisms (rs133333 and rs5758550) over 10,000 bases from CYP2D6 in the WW Binding Protein 2 N-terminal Like (WWBP2NL) locus that are associated with at least a two-fold increase in transcription of CYP2D6. The same group also characterized CYP2D6 distant enhancer polymorphisms that are significantly associated with variable expression of CYP2D6, which may ultimately influence rate of phase I drug metabolism (Wang, et al. 2015). Inclusion of gene expression regulators is still an underexplored area for pharmacogenomic studies involving $U G T 2 B 7, A B C B 1, O P R M 1$, and COMT; however, some studies have found interactions between polymorphisms in the target gene and its associated promoter and/or enhancer(s) resulting in varied gene expression (Wang, et al. 2013). It may be necessary to include additional elements (i.e., enhancers, micro RNA [miRNA] coding sites, and/or other genes) in the predictive model to improve accuracy.

The question of epigenetic modulation of drug metabolism has been proposed more recently as studies of miRNA activity and histone and DNA methylation studies discover disease and/or phenotype associated methylation signatures. Zeng, et al. (2017) identified a
miRNA (hsa-miR-370-3p) that participates in the degradation of CYP2D6, thereby modulating the efficacy of its substrates and contributing to potential idiosyncratic responses following drug administration. There are no studies suggesting that $U G T 2 B 7, A B C B 1$, or $O P R M 1$ have epigenetic regulation as a contributing factor to gene expression or enzyme activity. Conversely, COMT promoter hypomethylation has been correlated with positive selection of the Val158Met polymorphism that is commonly implicated in schizophrenia and bipolar disorder studies (Abdolmaleky, et al 2006). In addition, Park, et al. (2015) described differential expression of hepatic CYPs during fetal and adult stages of life. It is reasonable to hypothesize that similar regulatory patterns may exist within normal, rapid, and poor drug metabolizers either at the target gene itself or its associated regulatory elements.

Patient polypharmacy is a considerable limitation of clinical implementation of pharmacogenetic data because so few studies 1) recognize and include polypharmacy in their data analysis or 2) study the specific impact of multiple drug use on the phenotype of interest. Given the relatively broad activity of CYP2D6, it is reasonable to consider multiple drugs competing for active sites of the finite quantity of enzyme available in the body. Understanding the interplay between specific drug combinations commonly encountered (such as opioids plus benzodiazepines) will provide better support for implementing pharmacogenetic testing and ultimately provide more efficacious patient outcomes.

## Conclusions

In this dissertation, a novel pathway-driven model of tramadol pharmacogenetics was evaluated using supervised machine learning algorithms and a cohort of individuals from the Finnish population. The combined predictive power of a pathway driven model was superior
to that of the single gene model currently employed in many clinical applications. The future directions of this project should focus on evaluation of the model using other populations, cohorts exposed to non-tramadol opioids, and controlled combinations of opioids and additional compounds. The resulting model could be developed into a broadly-applicable and easily clinically implemented massively parallel sequencing library preparation panel for prediction of opioid response and guidance for prescription medication practices to ultimately reduce drug administration and/or dependence.

## References for Chapters 1 and 8

1000 Genomes Project Consortium, Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, Korbel JO, Marchini JL, McCarthy S, McVean GA, Abecasis GR. A global reference for human genetic variation. Nature. 2015 Oct 1;526(7571):68-74. doi: 10.1038/nature15393. PubMed PMID: 26432245; PubMed Central PMCID: PMC4750478.

Abdolmaleky HM, Cheng KH, Faraone SV, Wilcox M, Glatt SJ, Gao F, Smith CL, Shafa R, Aeali B, Carnevale J, Pan H, Papageorgis P, Ponte JF, Sivaraman V, Tsuang MT, Thiagalingam S. Hypomethylation of MB-COMT promoter is a major risk factor for schizophrenia and bipolar disorder. Hum Mol Genet. 2006 Nov 1;15(21):3132-45. Epub 2006 Sep 19. PubMed PMID: 16984965; PubMed Central PMCID: PMC2799943.

Alkan C, Sajjadian S, Eichler EE. Limitations of next-generation genome sequence assembly. Nature methods. 2011;8(1):61-65. doi:10.1038/nmeth. 1527.

Altar CA, Carhart JM, Allen JD, Hall-Flavin DK, Dechairo BM, Winner JG. Clinical validity: Combinatorial pharmacogenomics predicts antidepressant responses and healthcare utilizations better than single gene phenotypes. Pharmacogenomics J. 2015 Oct;15(5):443-51. doi: 10.1038/tpj.2014.85. Epub 2015 Feb 17. PubMed PMID: 25686762.

Ammar R, Paton TA, Torti D, Shlien A, Bader GD. Long read nanopore sequencing for detection of HLA and CYP2D6 variants and haplotypes. F1000Research. 2015;4:17.

Baber M, Chaudhry S, Kelly L, Ross C, Carleton B, Berger H, Koren G. The pharmacogenetics of codeine pain relief in the postpartum period. Pharmacogenomics J. 2015 Oct;15(5):430-5. doi: 10.1038/tpj.2015.3. Epub 2015 Mar 10. PubMed PMID: 25752520.

Barratt DT, Coller JK, Hallinan R, Byrne A, White JM, Foster DJ, Somogyi AA. ABCB1 haplotype and OPRM1 118A \> G genotype interaction in methadone maintenance treatment pharmacogenetics. Pharmgenomics Pers Med. 2012;5:53-62. doi: 10.2147/PGPM.S29272. PubMed PMID: 23226062; PubMed Central PMCID: PMC3513228.

Bastami S, Gupta A, Zackrisson AL, Ahlner J, Osman A, Uppugunduri S. Influence of UGT2B7, OPRM1 and ABCB1 gene polymorphisms on postoperative morphine consumption. Basic Clin Pharmacol Toxicol. 2014 Nov;115(5):423-31. doi: 10.1111/bcpt.12248. PubMed PMID: 24703092.

Beoris M, Amos Wilson J, Garces JA, Lukowiak AA. CYP2D6 copy number distribution in the US population. Pharmacogenet Genomics. 2016 Feb;26(2):96-9. doi: 10.1097/FPC.0000000000000188. PubMed PMID: 26551314; PubMed Central PMCID: PMC4704658.

BioPlex 2.0 Version 4. http://bioplex.hms.harvard.edu/bioplexDisplay/index.php. Accessed 19MAY2017.

Bock KW, Schrenk D, Forster A, Griese EU, Mörike K, Brockmeier D, Eichelbaum M. The influence of environmental and genetic factors on CYP2D6, CYP1A2 and UDPglucuronosyltransferases in man using sparteine, caffeine, and paracetamol as probes.Pharmacogenetics. 1994 Aug;4(4):209-18. PubMed PMID: 7987405.

Bodor M, Kelly EJ, Ho RJ. Characterization of the human MDR1 gene. AAPS J. 2005 Feb 16;7(1):E1-5. PubMed PMID: 16146331; PubMed Central PMCID: PMC2751491.

Børsting C, Morling N. Next generation sequencing and its applications in forensic genetics. Forensic Sci Int Genet. 2015 Sep;18:78-89. doi: 10.1016/j.fsigen.2015.02.002. Epub 2015 Feb 14.

Bradford LD. CYP2D6 allele frequency in European Caucasians, Asians, Africans and their descendants. Pharmacogenomics. 2002 Mar;3(2):229-43. Review. PubMed PMID: 11972444.

Bray NJ, Buckland PR, Williams NM, Williams HJ, Norton N, Owen MJ, O'Donovan MC. A haplotype implicated in schizophrenia susceptibility is associated with reduced COMT expression in human brain. Am J Hum Genet. 2003 Jul;73(1):152-61. PubMed PMID: 12802784; PubMed Central PMCID: PMC1180576.

Broly F, Meyer UA. Debrisoquine oxidation polymorphism: phenotypic consequences of a 3-base-pair deletion in exon 5 of the CYP2D6 gene. Pharmacogenetics. 1993 Jun;3(3):123-30. PubMed PMID: 8101460.

Browning SR, Browning BL. Haplotype phasing: existing methods and new developments. Nat Rev Genet. 2011;12:703-14.

Campa D, Gioia A, Tomei A, Poli P, Barale R. Association of ABCB1/MDR1 and OPRM1 gene polymorphisms with morphine pain relief. Clin Pharmacol Ther. 2008 Apr;83(4):559-66. PubMed PMID: 17898703.

Chen J, Lipska BK, Halim N, Ma QD, Matsumoto M, Melhem S, Kolachana BS, Hyde TM, Herman MM, Apud J, Egan MF, Kleinman JE, Weinberger DR. Functional analysis of genetic variation in catechol-O-methyltransferase (COMT): effects on mRNA, protein, and enzyme activity in postmortem human brain. Am J Hum Genet. 2004 Nov;75(5):807-21. Erratum in: Am J Hum Genet. 2005 Jun;76(6):1089. PubMed PMID: 15457404; PubMed Central PMCID: PMC1182110.

Chen R, Wang H, Shi J, Shen K, Hu P. Cytochrome P450 2D6 genotype affects the pharmacokinetics of controlled-release paroxetine in healthy Chinese subjects: comparison of traditional phenotype and activity score systems. Eur J Clin Pharmacol. 2015 Jul;71(7):83541. doi: 10.1007/s00228-015-1855-6. PubMed PMID: 25967538.

Christoffersen DJ, Damkier P, Feddersen S, Möller S, Thomsen JL, Brasch-Andersen C, Brøsen K. The ABCB1, rs9282564, AG and TT Genotypes and the COMT, rs4680, AA Genotype are Less Frequent in Deceased Patients with Opioid Addiction than in Living

Patients with Opioid Addiction. Basic Clin Pharmacol Toxicol. 2016 Oct;119(4):381-8. doi: 10.1111/bcpt.12602. PubMed PMID: 27061230.

Chung JY, Cho JY, Yu KS, Kim JR, Lim KS, Sohn DR, Shin SG, Jang IJ. Pharmacokinetic and pharmacodynamic interaction of lorazepam and valproic acid in relation to UGT2B7 genetic polymorphism in healthy subjects. Clin Pharmacol Ther. 2008 Apr;83(4):595-600. PubMed PMID: 17687269.

Contreras AV, Monge-Cazares T, Alfaro-Ruiz L, Hernandez-Morales S, Miranda-Ortiz H, Carrillo-Sanchez K, Jimenez-Sanchez G, Silva-Zolezzi I. Resequencing, haplotype construction and identification of novel variants of CYP2D6 in Mexican Mestizos. Pharmacogenomics. 2011 May;12(5):745-56. doi: 10.2217/pgs.11.8. PubMed PMID: 21391885.

Crews KR, Gaedigk A, Dunnenberger HM, Leeder JS, Klein TE, Caudle KE, Haidar CE, Shen DD, Callaghan JT, Sadhasivam S, Prows CA, Kharasch ED, Skaar TC; Clinical Pharmacogenetics Implementation Consortium. Clinical Pharmacogenetics Implementation Consortium guidelines for cytochrome P450 2D6 genotype and codeine therapy: 2014 update. Clin Pharmacol Ther. 2014 Apr;95(4):376-82. doi: 10.1038/clpt.2013.254. Epub 2014 Jan 23. Review. PubMed PMID: 24458010; PubMed Central PMCID: PMC3975212.

Crist RC, Berrettini WH. Pharmacogenetics of OPRM1. Pharmacol Biochem Behav. 2014 Aug;123:25-33. doi: 10.1016/j.pbb.2013.10.018. Epub 2013 Nov 5. Review. PubMed PMID: 24201053; PubMed Central PMCID: PMC4010567.

Cusato J, Tomasello C, Simiele M, Calcagno A, Bonora S, Marinaro L, Leggieri A, Allegra S, Di Perri G, D'Avolio A. Efavirenz pharmacogenetics in a cohort of Italian patients. Int J Antimicrob Agents. 2016 Feb;47(2):117-23. doi: 10.1016/j.ijantimicag.2015.11.012. PubMed PMID: 26774523.

Diatchenko L, Robinson JE, Maixner W. Elucidation of mu-Opioid Gene Structure: How Genetics Can Help Predict Responses to Opioids. Eur J Pain Suppl. 2011 Nov 11;5(2):433438. PubMed PMID: 22102848; PubMed Central PMCID: PMC3217294.

Diatchenko L, Slade GD, Nackley AG, Bhalang K, Sigurdsson A, Belfer I, Goldman D, Xu K, Shabalina SA, Shagin D, Max MB, Makarov SS, Maixner W. Genetic basis for individual variations in pain perception and the development of a chronic pain condition. Hum Mol Genet. 2005 Jan 1;14(1):135-43. Epub 2004 Nov 10. PubMed PMID: 15537663.

Du Z, Jiao Y, Shi L. Association of UGT2B7 and UGT1A4 Polymorphisms with Serum Concentration of Antiepileptic Drugs in Children. Med Sci Monit. 2016 Oct 31;22:4107-4113. PubMed PMID: 27795544; PubMed Central PMCID: PMC5100833.

Ebisawa A, Hiratsuka M, Sakuyama K, Konno Y, Sasaki T, Mizugaki M. Two novel single nucleotide polymorphisms (SNPs) of the CYP2D6 gene in Japanese individuals. Drug Metab Pharmacokinet. 2005 Aug;20(4):294-9. PubMed PMID: 16141609.

Eichelbaum M, Baur MP, Dengler HJ, Osikowska-Evers BO, Tieves G, Zekorn C, Rittner C. Chromosomal assignment of human cytochrome P-450 (debrisoquine/sparteine type) to chromosome 22. Br J Clin Pharmacol. 1987 Apr;23(4):455-8. PubMed PMID: 3472585; PubMed Central PMCID: PMC1386095.

Eichelbaum, M., Spannbrucker, N., Steincke, B. \& Dengler, H. J. Defective N-oxidation of sparteine in man: a new pharmacogenetic defect. Eur. J. Clin. Pharmacol. 16, 183-187 (1979).

Evans WE, Relling MV. Pharmacogenomics: translating functional genomics into rational therapeutics. Science. 1999 Oct 15;286(5439):487-91. Review. PubMed PMID: 10521338.

Feng Y, Zhang Y, Ying C, Wang D, Du C. Nanopore-based fourth-generation DNA sequencing technology. Genomics Proteomics Bioinformatics. 2015 Feb;13(1):4-16. doi: 10.1016/j.gpb.2015.01.009. Epub 2015 Mar 2. Review. Erratum in: Genomics Proteomics Bioinformatics. 2015 Dec;13(6):383. Genomics Proteomics Bioinformatics. 2015 Jun;13(3):200-201. PubMed PMID: 25743089; PubMed Central PMCID: PMC4411503.

Fox AL. The Relationship between Chemical Constitution and Taste. Proc Natl Acad Sci U S A. 1932 Jan;18(1):115-20. PubMed PMID: 16577421; PubMed Central PMCID: PMC1076170.

Fujita K, Ando Y, Yamamoto W, Miya T, Endo H, Sunakawa Y, Araki K, Kodama K, Nagashima F, Ichikawa W, Narabayashi M, Akiyama Y, Kawara K, Shiomi M, Ogata H, Iwasa H, Okazaki Y, Hirose T, Sasaki Y. Association of UGT2B7 and ABCB1 genotypes with morphine-induced adverse drug reactions in Japanese patients with cancer. Cancer Chemother Pharmacol. 2010 Jan;65(2):251-8. doi: 10.1007/s00280-009-1029-2. PubMed PMID: 19466410.

Gaedigk A, Blum M, Gaedigk R, Eichelbaum M, Meyer UA. Deletion of the entire cytochrome P450 CYP2D6 gene as a cause of impaired drug metabolism in poor metabolizers of the debrisoquine/sparteine polymorphism. Am J Hum Genet. 1991 May;48(5):943-50. PubMed PMID: 1673290; PubMed Central PMCID: PMC1683061.

Gaedigk A, Sangkuhl K, Whirl-Carrillo M, Klein T, Leeder JS. Prediction of CYP2D6 phenotype from genotype across world populations. Genet Med. 2016 Jul 7. doi: 10.1038/gim.2016.80. [Epub ahead of print] PubMed PMID: 27388693.

Gaedigk A, Simon SD, Pearce RE, Bradford LD, Kennedy MJ, Leeder JS. The CYP2D6 activity score: translating genotype information into a qualitative measure of phenotype. Clin Pharmacol Ther. 2008 Feb;83(2):234-42. Epub 2007 Oct 31. PubMed PMID: 17971818.

Garrod AE. The incidence of alkaptonuria: a study in chemical individuality. 1902. Mol Med. 1996 May;2(3):274-82. PubMed PMID: 8784780; PubMed Central PMCID: PMC2230159.

Goodwin S, McPherson JD, McCombie WR. Coming of age: ten years of next-generation sequencing technologies. Nat Rev Genet. 2016 May 17;17(6):333-51. doi: 10.1038/nrg.2016.49. Review. PubMed PMID: 27184599.

Gough AC, Smith CA, Howell SM, Wolf CR, Bryant SP, Spurr NK. Localization of the CYP2D gene locus to human chromosome 22q13.1 by polymerase chain reaction, in situ hybridization, and linkage analysis. Genomics. 1993 Feb;15(2):430-2. PubMed PMID: 8449513.

Guillemette C. Pharmacogenomics of human UDP-glucuronosyltransferase enzymes. Pharmacogenomics J. 2003;3(3):136-58. Review. PubMed PMID: 12815363.

Handoko HY, Nyholt DR, Hayward NK, Nertney DA, Hannah DE, Windus LC, McCormack CM, Smith HJ, Filippich C, James MR, Mowry BJ. Separate and interacting effects within the catechol-O-methyltransferase (COMT) are associated with schizophrenia. Mol Psychiatry. 2005 Jun;10(6):589-97. PubMed PMID: 15505638.

He X, He N, Ren L, Ouyang Y, Zhang N, Ma Y, Yuan D, Kang L, Jin T. Genetic polymorphisms analysis of CYP2D6 in the Uygur population. BMC Genomics. 2016 May 26;17:409. doi: 10.1186/s12864-016-2719-x. PubMed PMID: 27228982; PubMed Central PMCID: PMC4882831.

Hicks JK, Swen JJ, Thorn CF, Sangkuhl K, Kharasch ED, Ellingrod VL, Skaar TC, Müller DJ, Gaedigk A, Stingl JC; Clinical Pharmacogenetics Implementation Consortium. Clinical Pharmacogenetics Implementation Consortium guideline for CYP2D6 and CYP2C19 genotypes and dosing of tricyclic antidepressants. Clin Pharmacol Ther. 2013 May;93(5):4028. doi: 10.1038/clpt.2013.2. Epub 2013 Jan 16. Review. PubMed PMID: 23486447; PubMed Central PMCID: PMC3689226.

Hiratsuka M. In vitro assessment of the allelic variants of cytochrome P450. Drug Metab Pharmacokinet. 2012;27(1):68-84. Epub 2011 Nov 1. Review. PubMed PMID: 22041138.

Hodges LM, Markova SM, Chinn LW, Gow JM, Kroetz DL, Klein TE, Altman RB. Very important pharmacogene summary: ABCB1 (MDR1, P-glycoprotein). Pharmacogenet Genomics. 2011 Mar;21(3):152-61. doi: 10.1097/FPC.0b013e3283385a1c. PubMed PMID: 20216335; PubMed Central PMCID: PMC3098758.

Huttlin EL, Bruckner RJ, Paulo JA, Cannon JR, Ting L, Baltier K, Colby G, Gebreab F, Gygi MP, Parzen H, Szpyt J, Tam S, Zarraga G, Pontano-Vaites L, Swarup S, White AE, Schweppe DK, Rad R, Erickson BK, Obar RA, Guruharsha KG, Li K, Artavanis-Tsakonas S, Gygi SP, Harper JW. Architecture of the human interactome defines protein communities and disease networks. Nature. 2017 May 17. doi: 10.1038/nature22366. [Epub ahead of print] PubMed PMID: 28514442.

Ingelman-Sundberg M, Sim SC, Gomez A, Rodriguez-Antona C. Influence of cytochrome P450 polymorphisms on drug therapies: pharmacogenetic, pharmacoepigenetic and clinical
aspects.Pharmacol Ther. 2007 Dec;116(3):496-526. Epub 2007 Oct 9. Review. PubMed PMID: 18001838.

Ingelman-Sundberg M. Genetic polymorphisms of cytochrome P450 2D6 (CYP2D6): clinical consequences, evolutionary aspects and functional diversity. Pharmacogenomics J. 2005;5(1):6-13. Review. PubMed PMID: 15492763.

Ingelman-Sundberg M. Human drug metabolising cytochrome P450 enzymes: properties and polymorphisms. Naunyn Schmiedebergs Arch Pharmacol. 2004 Jan;369(1):89-104. Epub 2003 Oct 22. Review. PubMed PMID: 14574440.

Ip CLC, Loose M, Tyson JR, de Cesare M, Brown BL, Jain M, Leggett RM, Eccles DA, Zalunin V, Urban JM, Piazza P, Bowden RJ, Paten B, Mwaigwisya S, Batty EM, Simpson JT, Snutch TP, Birney E, Buck D, Goodwin S, Jansen HJ, O'Grady J, Olsen HE. MinION Analysis and Reference Consortium: Phase 1 data release and analysis. F1000Research. 2015;4:1075.

Jain M, Olsen HE, Paten B, Akeson M. The Oxford Nanopore MinION: delivery of nanopore sequencing to the genomics community. Genome Biol. 2016 Nov 25;17(1):239. Erratum in: Genome Biol. 2016 Dec 13;17 (1):256. PubMed PMID: 27887629; PubMed Central PMCID: PMC5124260.

Jain M, Olsen HE, Paten B, Akeson M. Erratum to: The Oxford Nanopore MinION: delivery of nanopore sequencing to the genomics community. Genome Biol. 2016 Dec 13;17(1):256. PubMed PMID: 27964738; PubMed Central PMCID: PMC5154158.

Janicki PK. Pharmacogenomics of pain management. Comprehensive treatment of chronic pain by medical, interventional, and integrative approaches. American Academy of Pain Medicine 2013. DOI 10.1007/978-1-4614-1560-2_2

Karolchik D, Hinrichs AS, Kent WJ. The UCSC Genome Browser. Curr Protoc Bioinformatics. 2012 Dec;Chapter 1:Unit1.4. doi: 10.1002/0471250953.bi0104s40. PubMed PMID: 23255150.

Kere J. Human population genetics: lessons from Finland. Annu Rev Genomics Hum Genet. 2001;2:103-28. Review. PubMed PMID: 11701645.

Kim RB, Leake BF, Choo EF, Dresser GK, Kubba SV, Schwarz UI, Taylor A, Xie HG, McKinsey J, Zhou S, Lan LB, Schuetz JD, Schuetz EG, Wilkinson GR. Identification of functionally variant MDR1 alleles among European Americans and African Americans. Clin Pharmacol Ther. 2001 Aug;70(2):189-99. PubMed PMID: 11503014.

Kimchi-Sarfaty C, Marple AH, Shinar S, Kimchi AM, Scavo D, Roma MI, Kim IW, Jones A, Arora M, Gribar J, Gurwitz D, Gottesman MM. Ethnicity-related polymorphisms and haplotypes in the human ABCB1 gene. Pharmacogenomics. 2007 Jan;8(1):29-39. PubMed PMID: 17187507; PubMed Central PMCID: PMC1876748.

Kimura S, Umeno M, Skoda RC, Meyer UA, Gonzalez FJ. The human debrisoquine 4hydroxylase (CYP2D) locus: sequence and identification of the polymorphic CYP2D6 gene, a related gene, and a pseudogene. Am J Hum Genet. 1989 Dec;45(6):889-904. PubMed PMID: 2574001; PubMed Central PMCID: PMC1683468.

Knapman A, Connor M. Cellular signalling of non-synonymous single-nucleotide polymorphisms of the human $\mu$-opioid receptor (OPRM1). Br J Pharmacol. 2015 Jan;172(2):349-63. doi: 10.1111/bph.12644. Epub 2014 Jul 1. Review. PubMed PMID: 24527749; PubMed Central PMCID: PMC4292952.

Koch WH. Technology platforms for pharmacogenomic diagnostic assays. Nat Rev Drug Discov. 2004 Sep;3(9):749-61. Review. PubMed PMID: 15340385.

Kong A, Masson G, Frigge ML, Gylfason A, Zusmanovich P, Thorleifsson G, Olason PI, Ingason A, Steinberg S, Rafnar T, Sulem P, Mouy M, Jonsson F, Thorsteinsdottir U, Gudbjartsson DF, Stefansson H, Stefansson K. Detection of sharing by descent, long-range phasing and haplotype imputation. Nature genetics. 2008;40:1068-75.

Koren G, Cairns J, Chitayat D, Gaedigk A, Leeder SJ. Pharmacogenetics of morphine poisoning in a breastfed neonate of a codeine-prescribed mother. Lancet. 2006 Aug 19;368(9536):704. PubMed PMID: 16920476.

Kroetz DL, Pauli-Magnus C, Hodges LM, Huang CC, Kawamoto M, Johns SJ, Stryke D, Ferrin TE, DeYoung J, Taylor T, Carlson EJ, Herskowitz I, Giacomini KM, Clark AG; Pharmacogenetics of Membrane Transporters Investigators.. Sequence diversity and haplotype structure in the human ABCB1 (MDR1, multidrug resistance transporter) gene. Pharmacogenetics. 2003 Aug;13(8):481-94. Erratum in: Pharmacogenetics. 2003 Nov;13(11):701. PubMed PMID: 12893986.

Lachance J, Tishkoff SA. SNP ascertainment bias in population genetic analyses: why it is important, and how to correct it. Bioessays. 2013 Sep;35(9):780-6. doi: 10.1002/bies.201300014. Epub 2013 Jul 9. Review. PubMed PMID: 23836388; PubMed Central PMCID: PMC3849385.

Lachman HM, Papolos DF, Saito T, Yu YM, Szumlanski CL, Weinshilboum RM. Human catechol-O-methyltransferase pharmacogenetics: description of a functional polymorphism and its potential application to neuropsychiatric disorders. Pharmacogenetics. 1996 Jun;6(3):243-50. PubMed PMID: 8807664.

Lam J, Woodall KL, Solbeck P, Ross CJ, Carleton BC, Hayden MR, et al. Codeine-related deaths: The role of pharmacogenetics and drug interactions. Forensic Sci Int. 2014 Jun;239:506. doi: 10.1016/j.forsciint.2014.03.018. Epub 2014 Mar 26. PubMed PMID: 24747667.

Leathart JB, London SJ, Steward A, Adams JD, Idle JR, Daly AK. CYP2D6 phenotypegenotype relationships in African-Americans and Caucasians in Los Angeles. Pharmacogenetics. 1998 Dec;8(6):529-41. PubMed PMID: 9918137.

Leppert W. CYP2D6 in the metabolism of opioids for mild to moderate pain. Pharmacology. 2011;87(5-6):274-85. doi: 10.1159/000326085. Epub 2011 Apr 15. Review. PubMed PMID: 21494059.

Leschziner GD, Andrew T, Pirmohamed M, Johnson MR. ABCB1 genotype and PGP expression, function and therapeutic drug response: a critical review and recommendations for future research. Pharmacogenomics J. 2007 Jun;7(3):154-79. Review. PubMed PMID: 16969364.

Levy SE, Myers RM. Advancements in Next-Generation Sequencing. Annu Rev Genomics Hum Genet. 2016 Aug 31;17:95-115. doi: 10.1146/annurev-genom-083115-022413. Epub 2016 Jun 9. PubMed PMID: 27362342.

Lewis DF. 57 varieties: the human cytochromes P450. Pharmacogenomics. 2004 Apr;5(3):305-18. Review. PubMed PMID: 15102545.

Lindberg MR, Schmedes SE, Hewitt FC, Haas JL, Ternus KL, Kadavy DR, Budowle B. A Comparison and Integration of MiSeq and MinION Platforms for Sequencing Single Source and Mixed Mitochondrial Genomes. PloS one. 2016;11:e0167600.

Lim ET, Würtz P, Havulinna AS, Palta P, Tukiainen T, Rehnström K, Esko T, Mägi R, Inouye M, Lappalainen T, Chan Y, Salem RM, Lek M, Flannick J, Sim X, Manning A, Ladenvall C, Bumpstead S, Hämäläinen E, Aalto K, Maksimow M, Salmi M, Blankenberg S, Ardissino D, Shah S, Horne B, McPherson R, Hovingh GK, Reilly MP, Watkins H, Goel A, Farrall M, Girelli D, Reiner AP, Stitziel NO, Kathiresan S, Gabriel S, Barrett JC, Lehtimäki T, Laakso M, Groop L, Kaprio J, Perola M, McCarthy MI, Boehnke M, Altshuler DM, Lindgren CM, Hirschhorn JN, Metspalu A, Freimer NB, Zeller T, Jalkanen S, Koskinen S, Raitakari O, Durbin R, MacArthur DG, Salomaa V, Ripatti S, Daly MJ, Palotie A; Sequencing Initiative Suomi (SISu) Project.. Distribution and medical impact of loss-of-function variants in the Finnish founder population. PLoS Genet. 2014 Jul 31;10(7):e1004494. doi: 10.1371/journal.pgen.1004494. PubMed PMID: 25078778; PubMed Central PMCID: PMC4117444.

Lotta T, Vidgren J, Tilgmann C, Ulmanen I, Melén K, Julkunen I, Taskinen J. Kinetics of human soluble and membrane-bound catechol O-methyltransferase: a revised mechanism and description of the thermolabile variant of the enzyme. Biochemistry. 1995 Apr 4;34(13):420210. PubMed PMID: 7703232.

Lu H, Giordano F, Ning Z. Oxford Nanopore MinION Sequencing and Genome Assembly. Genomics Proteomics Bioinformatics. 2016 Oct;14(5):265-279. doi: 10.1016/j.gpb.2016.05.004. Epub 2016 Sep 17. Review. PubMed PMID: 27646134; PubMed Central PMCID: PMC5093776.

Luzzatto L, Nannelli C, Notaro R. Glucose-6-Phosphate Dehydrogenase Deficiency. Hematol Oncol Clin North Am. 2016 Apr;30(2):373-93. doi: 10.1016/j.hoc.2015.11.006. Review. PubMed PMID: 27040960.

Lysholm F, Andersson B, Persson B. FAAST: Flow-space Assisted Alignment Search Tool. BMC Bioinformatics. 2011 Jul 19;12:293. doi: 10.1186/1471-2105-12-293. PubMed PMID: 21771335; PubMed Central PMCID: PMC3228549.

Marchini J, Cutler D, Patterson N, Stephens M, Eskin E, Halperin E, Lin S, Qin ZS, Munro HM, Abecasis GR, Donnelly P. A comparison of phasing algorithms for trios and unrelated individuals. Am J Hum Genet. 2006;78:437-50.

Marez D, Legrand M, Sabbagh N, Lo Guidice JM, Spire C, Lafitte JJ, Meyer UA, Broly F. Polymorphism of the cytochrome P450 CYP2D6 gene in a European population: characterization of 48 mutations and 53 alleles, their frequencies and evolution. Pharmacogenetics. 1997 Jun;7(3):193-202. PubMed PMID: 9241659.

Marez D, Legrand M, Sabbagh N, Lo-Guidice JM, Boone P, Broly F. An additional allelic variant of the CYP2D6 gene causing impaired metabolism of sparteine. Hum Genet. 1996 May;97(5):668-70. PubMed PMID: 8655150.

Marez D, Sabbagh N, Legrand M, Lo-Guidice JM, Boone P, Broly F. A novel CYP2D6 allele with an abolished splice recognition site associated with the poor metabolizer phenotype. Pharmacogenetics. 1995 Oct;5(5):305-11. PubMed PMID: 8563771.

Mathijssen RH, Marsh S, Karlsson MO, Xie R, Baker SD, Verweij J, Sparreboom A, McLeod HL. Irinotecan pathway genotype analysis to predict pharmacokinetics. Clin Cancer Res. 2003 Aug 15;9(9):3246-53. PubMed PMID: 12960109.

Meletis, JC. Favism: A brief history from the "abstain from beans" of Pythagoras to the present. Arch Hellenic Med 29:258-263. 2011 Nov 30.

Meyer UA. Pharmacogenetics - five decades of therapeutic lessons from genetic diversity. Nat Rev Genet. 2004 Sep;5(9):669-76. Review. PubMed PMID: 15372089.

Modaresi-Nejad M, Shiva M, Afsharian P. Novel +90G\>A Intronic Polymorphism of CYP2D6. Cell J. 2015 Spring;17(1):83-8. PubMed PMID: 25870837; PubMed Central PMCID: PMC4393675.

Narula N, Tester DJ, Paulmichl A, Maleszewski JJ, Ackerman MJ. Post-mortem Whole exome sequencing with gene-specific analysis for autopsy-negative sudden unexplained death in the young: a case series. Pediatr Cardiol. 2015 Apr;36(4):768-78. doi: 10.1007/s00246-014-10824. Epub 2014 Dec 13. PubMed PMID: 25500949; PubMed Central PMCID: PMC4907366.

Ortiz de Montellano, Paul R.; Paul R. Ortiz de Montellano (2005). Cytochrome P450: structure, mechanism, and biochemistry (3rd ed.). New York: Kluwer Academic/Plenum Publishers. ISBN 0-306-48324-6.

Palo JU, Ulmanen I, Lukka M, Ellonen P, Sajantila A. Genetic markers and population history: Finland revisited. Eur J Hum Genet. 2009 Oct;17(10):1336-46. doi: 10.1038/ejhg.2009.53. Epub 2009 Apr 15. PubMed PMID: 19367325; PubMed Central PMCID: PMC2986642.

Park HJ, Choi YJ, Kim JW, Chun HS, Im I, Yoon S, Han YM, Song CW, Kim H. Differences in the Epigenetic Regulation of Cytochrome P450 Genes between Human Embryonic Stem Cell-Derived Hepatocytes and Primary Hepatocytes. PLoS One. 2015 Jul 15;10(7):e0132992. doi: 10.1371/journal.pone.0132992. eCollection 2015. PubMed PMID: 26177506; PubMed Central PMCID: PMC4503736.

Peltonen L, Jalanko A, Varilo T. Molecular genetics of the Finnish disease heritage. Hum Mol Genet. 1999;8(10):1913-23. Review. PubMed PMID: 10469845.

Pharmacogenomics Knowledgebase.
https://www.pharmgkb.org/gene/PA267?tabType=tabVip\#tabview=tab4\&subtab=
Polimanti R, Piacentini S, Manfellotto D, Fuciarelli M. Human genetic variation of CYP450 superfamily: analysis of functional diversity in worldwide populations. Pharmacogenomics. 2012 Dec;13(16):1951-60. doi: 10.2217/pgs.12.163. PubMed PMID: 23215887.

Quail MA, Smith M, Coupland P, Otto TD, Harris SR, Connor TR, Bertoni A, Swerdlow HP, Gu Y. A tale of three next generation sequencing platforms: comparison of Ion Torrent, Pacific Biosciences and Illumina MiSeq sequencers. BMC Genomics. 2012 Jul 24;13:341. doi: 10.1186/1471-2164-13-341. PubMed PMID: 22827831; PubMed Central PMCID: PMC3431227.

Rakvåg TT, Klepstad P, Baar C, Kvam TM, Dale O, Kaasa S, Krokan HE, Skorpen F. The Val158Met polymorphism of the human catechol-O-methyltransferase (COMT) gene may influence morphine requirements in cancer pain patients. Pain. 2005 Jul;116(1-2):73-8. PubMed PMID: 15927391.

Ritter JK, Sheen YY, Owens IS. Cloning and expression of human liver UDPglucuronosyltransferase in COS-1 cells. 3,4-catechol estrogens and estriol as primary substrates. J Biol Chem. 1990 May 15;265(14):7900-6. PubMed PMID: 2159463.

Ross JR, Riley J, Taegetmeyer AB, Sato H, Gretton S, du Bois RM, Welsh KI. Genetic variation and response to morphine in cancer patients: catechol-O-methyltransferase and multidrug resistance-1 gene polymorphisms are associated with central side effects. Cancer. 2008 Mar 15;112(6):1390-403. doi: 10.1002/cncr.23292. PubMed PMID: 18257092.

Sachse C, Brockmöller J, Bauer S, Roots I. Cytochrome P450 2D6 variants in a Caucasian population: allele frequencies and phenotypic consequences. Am J Hum Genet. 1997 Feb;60(2):284-95. PubMed PMID: 9012401; PubMed Central PMCID: PMC1712396.

Saeki M, Saito Y, Jinno H, Tanaka-Kagawa T, Ohno A, Ozawa S, Ueno K, Kamakura S, Kamatani N, Komamura K, Kitakaze M, Sawada J. Single nucleotide polymorphisms and haplotype frequencies of UGT2B4 and UGT2B7 in a Japanese population. Drug Metab Dispos. 2004 Sep;32(9):1048-54. PubMed PMID: 15319348.

Sakuyama K, Sasaki T, Ujiie S, Obata K, Mizugaki M, Ishikawa M, Hiratsuka M. Functional characterization of 17 CYP2D6 allelic variants (CYP2D6.2, 10, 14A-B, 18, 27, 36, 39, 47-51, 53-55, and 57). Drug Metab Dispos. 2008 Dec;36(12):2460-7. doi: 10.1124/dmd.108.023242. PubMed PMID: 18784265.

Sawyer MB, Innocenti F, Das S, Cheng C, Ramírez J, Pantle-Fisher FH, Wright C, Badner J, Pei D, Boyett JM, Cook E Jr, Ratain MJ. A pharmacogenetic study of uridine diphosphateglucuronosyltransferase 2B7 in patients receiving morphine. Clin Pharmacol Ther. 2003 Jun;73(6):566-74. PubMed PMID: 12811366.

Schacht JP. COMT val158met moderation of dopaminergic drug effects on cognitive function: a critical review. Pharmacogenomics J. 2016 Oct;16(5):430-8. doi: 10.1038/tpj.2016.43. Review. PubMed PMID: 27241058; PubMed Central PMCID: PMC5028240.

Schaich M, Kestel L, Pfirrmann M, Robel K, Illmer T, Kramer M, Dill C, Ehninger G, Schackert G, Krex D. A MDR1 (ABCB1) gene single nucleotide polymorphism predicts outcome of temozolomide treatment in glioblastoma patients. Ann Oncol. 2009 Jan;20(1):17581. doi: 10.1093/annonc/mdn548. PubMed PMID: 18687982.

Sistonen J, Madadi P, Ross CJ, Yazdanpanah M, Lee JW, Landsmeer ML, Nauta M, Carleton BC, Koren G, Hayden MR. Prediction of codeine toxicity in infants and their mothers using a novel combination of maternal genetic markers. Clin Pharmacol Ther. 2012 Apr;91(4):692-9. doi: 10.1038/clpt.2011.280. Epub 2012 Mar 7. PubMed PMID: 22398969.

Sistonen J, Sajantila A, Lao O, Corander J, Barbujani G, Fuselli S. CYP2D6 worldwide genetic variation shows high frequency of altered activity variants and no continental structure. Pharmacogenet Genomics. 2007 Feb;17(2):93-101. PubMed PMID: 17301689.

Skierka JM, Walker DL, Peterson SE, O'Kane DJ, Black JL 3rd. CYP2D6*11 and challenges in clinical genotyping of the highly polymorphic CYP2D6 gene. Pharmacogenomics. 2012 Jun;13(8):951-4. doi: 10.2217/pgs.12.56. PubMed PMID: 22676198.

Skinner JR, Crawford J, Smith W, Aitken A, Heaven D, Evans CA, Hayes I, Neas KR, Stables S, Koelmeyer T, Denmark L, Vuletic J, Maxwell F, White K, Yang T, Roden DM, Leren TP, Shelling A, Love DR; Cardiac Inherited Disease Group New Zealand.. Prospective, population-based long QT molecular autopsy study of postmortem negative sudden death in 1
to 40 year olds. Heart Rhythm. 2011 Mar;8(3):412-9. doi: 10.1016/j.hrthm.2010.11.016. Epub 2010 Nov 9. PubMed PMID: 21070882.

Slaughter RL, Edwards DJ. Recent advances: the cytochrome P450 enzymes. Ann Pharmacother. 1995 Jun;29(6):619-24. Review. PubMed PMID: 7663035.

Smith, R. L. Introduction: human genetic variations in oxidative drug metabolism. Xenobiotica 16, 361-365 (1986).

Sridharan K, Kataria R, Tolani D, Bendkhale S, Gogtay NJ, Thatte UM. Evaluation of CYP2C19, P2Y12, and ABCB1 polymorphisms and phenotypic response to clopidogrel in healthy Indian adults. Indian J Pharmacol. 2016 Jul-Aug;48(4):350-354. PubMed PMID: 27756942; PubMed Central PMCID: PMC4980919.

Steen VM, Andreassen OA, Daly AK, Tefre T, Børresen AL, Idle JR, Gulbrandsen AK. Detection of the poor metabolizer-associated CYP2D6(D) gene deletion allele by long-PCR technology. Pharmacogenetics. 1995 Aug;5(4):215-23. PubMed PMID: 8528268.

Sutiman N, Lim JS, Muerdter TE, Singh O, Cheung YB, Ng RC, Yap YS, Wong NS, Ang PC, Dent R, Schroth W, Schwab M, Khor CC, Chowbay B. Pharmacogenetics of UGT1A4, UGT2B7 and UGT2B15 and Their Influence on Tamoxifen Disposition in Asian Breast Cancer Patients. Clin Pharmacokinet. 2016 Oct;55(10):1239-50. doi: 10.1007/s40262-016-0402-7. PubMed PMID: 27098059.

Teo YY, Fry AE, Clark TG, Tai ES, Seielstad M. On the usage of HWE for identifying genotyping errors. Ann Hum Genet. 2007 Sep;71(Pt 5):701-3; author reply 704. PubMed PMID: 17388941.

Tester DJ, Spoon DB, Valdivia HH, Makielski JC, Ackerman MJ. Targeted mutational analysis of the RyR2-encoded cardiac ryanodine receptor in sudden unexplained death: a molecular autopsy of 49 medical examiner/coroner's cases. Mayo Clin Proc. 2004 Nov;79(11):1380-4. PubMed PMID: 15544015.

Tester DJ, Ackerman MJ. The role of molecular autopsy in unexplained sudden cardiac death. Curr Opin Cardiol. 2006 May;21(3):166-72. Review. PubMed PMID: 16601452.

Ting S, Schug S. The pharmacogenomics of pain management: prospects for personalized medicine. J Pain Res. 2016 Feb 10;9:49-56. doi: 10.2147/JPR.S55595. Review. PubMed PMID: 26929662; PubMed Central PMCID: PMC4755469.

Vandenbossche J, Richards H, Francke S, Van Den Bergh A, Lu CC, Franc MA. The effect of UGT2B7*2 polymorphism on the pharmacokinetics of OROS® hydromorphone in Taiwanese subjects. J Clin Pharmacol. 2014 Oct;54(10):1170-9. doi: 10.1002/jcph.305. PubMed PMID: 24706503.

Waldhoer M, Bartlett SE, Whistler JL. Opioid receptors. Annu Rev Biochem. 2004;73:95390. Review. PubMed PMID: 15189164.

Wang D, Johnson AD, Papp AC, Kroetz DL, Sadée W. Multidrug resistance polypeptide 1 (MDR1, ABCB1) variant 3435C\>T affects mRNA stability. Pharmacogenet Genomics. 2005 Oct;15(10):693-704. PubMed PMID: 16141795.

Wang D, Papp AC, Sun X. Functional characterization of CYP2D6 enhancer polymorphisms. Hum Mol Genet. 2015 Mar 15;24(6):1556-62. doi: $10.1093 / \mathrm{hmg} / \mathrm{ddu} 566$. PubMed PMID: 25381333; PubMed Central PMCID: PMC4381757.

Wang D, Poi MJ, Sun X, Gaedigk A, Leeder JS, Sadee W. Common CYP2D6 polymorphisms affecting alternative splicing and transcription: long-range haplotypes with two regulatory variants modulate CYP2D6 activity. Hum Mol Genet. 2014 Jan 1;23(1):268-78. doi: 10.1093/hmg/ddt417. PubMed PMID: 23985325; PubMed Central PMCID: PMC3857955.

Wang H, Yuan L, Zeng S. Characterizing the effect of UDP-glucuronosyltransferase (UGT) 2B7 and UGT1A9 genetic polymorphisms on enantioselective glucuronidation of flurbiprofen. Biochem Pharmacol. 2011 Dec 1;82(11):1757-63. doi: 10.1016/j.bcp.2011.08.004. PubMed PMID: 21856293.

Wang PY, Huo D, Sun C, Olopade OI. The use of allelic imbalance to ascertain cis-regulation for human UGT2B7 in vivo. Eur J Clin Pharmacol. 2013 Sep;69(9):1733-5. doi: 10.1007/s00228-013-1538-0. Epub 2013 Jun 6. PubMed PMID: 23740002; PubMed Central PMCID: PMC3748163.

Wang SL, Lai MD, Huang JD. G169R mutation diminishes the metabolic activity of CYP2D6 in Chinese. Drug Metab Dispos. 1999 Mar;27(3):385-8. PubMed PMID: 10064570.

Weber A, Szalai R, Sipeky C, Magyari L, Melegh M, Jaromi L, Matyas P, Duga B, Kovesdi E, Hadzsiev K, Melegh B. Increased prevalence of functional minor allele variants of drug metabolizing CYP2B6 and CYP2D6 genes in Roma population samples. Pharmacol Rep. 2015 Jun;67(3):460-4. doi: 10.1016/j.pharep.2014.11.006. Epub 2014 Nov 27. PubMed PMID: 25933954.

Webster LR. Pharmacogenetics in pain management: the clinical need. Clin Lab Med. 2008 Dec;28(4):569-79. doi: 10.1016/j.cll.2008.05.005. Review. PubMed PMID: 19059063.

Wooding S. Phenylthiocarbamide: a 75-year adventure in genetics and natural selection. Genetics. 2006 Apr;172(4):2015-23. PubMed PMID: 16636110; PubMed Central PMCID: PMC1456409.

Wu AHB, White MJ, Oh S, Burchard E. The Hawaii clopidogrel lawsuit: the possible effect on clinical laboratory testing. Per Med. 2015 12(3), 179-181. ISSN 1741-0541.

Xin L, Wang ZJ. Bioinformatic analysis of the human mu opioid receptor (OPRM1) splice and polymorphic variants. AAPS PharmSci. 2002;4(4):E23. PubMed PMID: 12645995; PubMed Central PMCID: PMC2751312.

Yokoi T, Kosaka Y, Chida M, Chiba K, Nakamura H, Ishizaki T, Kinoshita M, Sato K, Gonzalez FJ, Kamataki T. A new CYP2D6 allele with a nine base insertion in exon 9 in a Japanese population associated with poor metabolizer phenotype. Pharmacogenetics. 1996 Oct;6(5):395-401. PubMed PMID: 8946471.

Yuan L, Qian S, Xiao Y, Sun H, Zeng S. Homo- and hetero-dimerization of human UDPglucuronosyltransferase 2B7 (UGT2B7) wild type and its allelic variants affect zidovudine glucuronidation activity. Biochem Pharmacol. 2015 May 1;95(1):58-70. doi: 10.1016/j.bcp.2015.03.002. PubMed PMID: 25770680.

Yuferov V, Levran O, Proudnikov D, Nielsen DA, Kreek MJ. Search for genetic markers and functional variants involved in the development of opiate and cocaine addiction and treatment. Ann N Y Acad Sci. 2010 Feb;1187:184-207. doi: 10.1111/j.1749-6632.2009.05275.x. Review. PubMed PMID: 20201854; PubMed Central PMCID: PMC3769182.

Zahari Z, Lee CS, Ibrahim MA, Musa N, Mohd Yasin MA, Lee YY, Tan SC, Mohamad N, Ismail R. Relationship Between ABCB1 Polymorphisms and Cold Pain Sensitivity Among Healthy Opioid-Naive Malay Males. Pain Pract. 2016 Dec 20. doi: 10.1111/papr.12546. [Epub ahead of print] PubMed PMID: 27996183.

Zeng L, Chen Y, Wang Y, Yu LR, Knox B, Chen J, Shi T, Chen S, Ren Z, Guo L, Wu Y, Liu D, Huang K, Tong W, Yu D, Ning B. MicroRNA hsa-miR-370-3p suppresses the expression and induction of CYP2D6 by facilitating mRNA degradation. Biochem Pharmacol. 2017 Sep 15;140:139-149. doi: 10.1016/j.bcp.2017.05.018. Epub 2017 May 26. PubMed PMID: 28552654.

Zhang YT, Yang LP, Shao H, Li KX, Sun CH, Shi LW. ABCB1 polymorphisms may have a minor effect on ciclosporin blood concentrations in myasthenia gravis patients. Br J Clin Pharmacol. 2008 Aug;66(2):240-6. doi: 10.1111/j.1365-2125.2008.03180.x. PubMed PMID: 18717915; PubMed Central PMCID: PMC2492911.

Zhou SF, Di YM, Chan E, Du YM, Chow VD, Xue CC, Lai X, Wang JC, Li CG, Tian M, Duan W. Clinical pharmacogenetics and potential application in personalized medicine. Curr Drug Metab. 2008 Oct;9(8):738-84. Review. PubMed PMID: 18855611.

Zhou SF. Polymorphism of human cytochrome P450 2D6 and its clinical significance: Part I. Clin Pharmacokinet. 2009;48(11):689-723. doi: 10.2165/11318030-0000000000-00000. Review. PubMed PMID: 19817501.

Zubieta JK, Heitzeg MM, Smith YR, Bueller JA, Xu K, Xu Y, Koeppe RA, Stohler CS, Goldman D. COMT val158met genotype affects mu-opioid neurotransmitter responses to a pain stressor. Science. 2003 Feb 21;299(5610):1240-3. PubMed PMID: 12595695.

1000 Genomes Project Consortium, Auton A, Brooks LD, Durbin RM, Garrison EP, Kang HM, et al. A global reference for human genetic variation. Nature. 2015 Oct 1;526(7571):6874. doi: 10.1038/nature 15393. PubMed PMID: 26432245; PubMed Central PMCID: PMC4750478.

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## APPENDIX D

## LIST OF PUBLICATIONS

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*Wendt FR, Novroski NMM, Rahikainen AL, Sajantila A, Budowle B. A pathway-driven predictive model of tramadol metabolism. European Journal of Human Genetics. In Review.

Woerner AE, Ambers A, Wendt FR, King JL, Budowle B. Complete mitochondrial genome sequencing with the Precision ID Whole mtDNA Genome Panel on the MiSeq. Forensic Science International: Genetics. In Review.
*Wendt FR, Rahikainen AL, King JL, Sajantila A, Budowle B. A genome-wide association study of tramadol metabolism from post-mortem samples. Legal Medicine. In Review.
*Wendt FR, Novroski NMM, Rahikainen AL, Sajantila A, Budowle B. Supervised classification of CYP2D6 metabolizer phenotype with tramadol-exposed Finns. International Journal of Legal Medicine. In Review.

Fried C, Bretell TA, Wendt FR, Pritchett TH. Atmospheric pressure chemical ionization tandem mass spectrometry and syringe liquid infusion method for the screening of ignitable liquids in fire debris samples. Forensic Chemistry. In Review.

Wendt FR, Woerner AE, Sajantila A, Moura-Neto RS, Budowle B. Exploring the 1000 Genomes Project haplotype reporting for the CYP2D6 pharmacogene. Int J Legal Med. 2018 Jun 2. doi: 10.1007/s00414-018-1874-9. [Epub ahead of print] PubMed PMID: 29860596.
*Wendt FR, Sajantila A, Budowle B. Predicted activity of UGT2B7, ABCB1, OPRM1, and COMT using full-gene haplotypes and their association with the CYP2D6-inferred metabolizer phenotype. Forensic Sci Int Genet. 2017 Nov 26;33:48-58. doi: 10.1016/j.fsigen.2017.11.012. [Epub ahead of print] PubMed PMID: 29190510.

Schmedes SE, Woerner AE, Novroski NMM, Wendt FR, King JL, Budowle B. Targeted sequencing of clade-specific markers from skin microbiomes for forensic human identification. Forensic Sci Int Genet. 2017 Oct 17. doi: http://dx.doi.org/10.1016/j.fsigen.2017.10.004.
*Wendt FR, Sajantila A, Moura-Neto RS, Woerner AE, Budowle B. Full-gene haplotypes refine CYP2D6 metabolizer phenotype inferences. Int J Legal Med. 2017 Oct 26. doi: 10.1007/s00414-017-1709-0. [Epub ahead of print] PubMed PMID: 29075918.

Moura-Neto RS, Mello ICT, Silva R, Maette APC, Bottino CG, Woerner A, King J, Wendt F, Budowle B. Evaluation of InnoTyper ${ }^{\circledR} 21$ in a sample of Rio de Janeiro population as an alternative forensic panel. Int J Legal Med. 2017 Jul 26. doi: 10.1007/s00414-017-1642-2. [Epub ahead of print] PubMed PMID: 28748403.

Budowle B, Schmedes SE, Wendt FR. Increasing the reach of forensic genetics with massively parallel sequencing. Forensic Sci Med Pathol. 2017 Jun 19. doi: 10.1007/s12024-017-9882-5. [Epub ahead of print] Review. PubMed PMID: 28631109.

Brown H, Thompson R, Murphy G, Peters D, LaRue B, King J, Montgomery AH, Carroll M, Baus J, Sinha S, Wendt FR, Song B, Chakraborty R, Budowle B, Sinha SK. Development and validation of a novel multiplexed DNA analysis system, InnoTyper® 21. Forensic Sci Int Genet. 2017 Mar 18;29:80-99. doi: 10.1016/j.fsigen.2017.03.017. [Epub ahead of print] PubMed PMID: 28391141.

King JL, Wendt FR, Sun J, Budowle B. STRait Razor v2s: Advancing sequence-based STR allele reporting and beyond to other marker systems. Forensic Sci Int Genet. 2017 Mar 12;29:21-28. doi: 10.1016/j.fsigen.2017.03.013. [Epub ahead of print] PubMed PMID: 28343097.

Wendt FR, King JL, Novroski NM, Churchill JD, Ng J, Oldt RF, McCulloh KL, Weise JA, Smith DG, Kanthaswamy S, Budowle B. Flanking region variation of ForenSeq ${ }^{\text {TM }}$ DNA Signature Prep Kit STR and SNP loci in Yavapai Native Americans. Forensic Sci Int Genet. 2017 May;28:146-154. doi: 10.1016/j.fsigen.2017.02.014. Epub 2017 Feb 27. PubMed PMID: 28273507.
*Wendt FR, Pathak G, Sajantila A, Chakraborty R, Budowle B. Global genetic variation of select opiate metabolism genes in self-reported healthy individuals. Pharmacogenomics J. 2017 Apr 11. doi: 10.1038/tpj.2017.13. [Epub ahead of print] PubMed PMID: 28398354.

Pakstis AJ, Kang L, Liu L, Zhang Z, Jin T, Grigorenko EL, Wendt FR, Budowle B, Hadi S, Al Qahtani MS, Morling N, Mogensen HS, Themudo GE, Soundararajan U, Rajeevan H, Kidd JR, Kidd KK. Increasing the reference populations for the 55 AISNP panel: the need and benefits. Int J Legal Med. 2017 Jul;131(4):913-917. doi: 10.1007/s00414-016-1524-z. Epub 2017 Jan 9. PubMed PMID: 28070634; PubMed Central PMCID: PMC5491587.

Wendt FR, Warshauer DH, Zeng X, Churchill JD, Novroski NM, Song B, King JL, LaRue BL, Budowle B. Massively parallel sequencing of 68 insertion/deletion markers identifies novel microhaplotypes for utility in human identity testing. Forensic Sci Int Genet. 2016 Nov;25:198-209. doi: 10.1016/j.fsigen.2016.09.005. PubMed PMID: 27685342.

Wendt FR, Churchill JD, Novroski NMM, King JL, Ng J, Oldt RF, McCulloh KL, Weise JA, Smith DG, Kanthaswamy S, Budowle B. Genetic analysis of the Yavapai Native Americans from West-Central Arizona using the Illumina MiSeq FGx ${ }^{\mathrm{TM}}$ Forensic Genomics System. Forensic Sci Int Genet. 2016 Sep;24:18-23. doi: 10.1016/j.fsigen.2016.05.008. Epub 2016 May 17. PubMed PMID: 27243782.

Wendt FR, Zeng X, Churchill JD, King JL, Budowle B. Analysis of short tandem repeat and single nucleotide polymorphism loci from single-source samples using a custom HaloPlex Target Enrichment System panel. Am J Forensic Med Pathol. 2016 Jun;37(2):99-107. doi: 10.1097/PAF.0000000000000228. PubMed PMID: 27075592.

Holland M, Wendt FR. Evaluation of the RapidHIT ${ }^{\text {TM }} 200$, an automated human identification system for STR analysis of single source samples. Forensic Sci Int Genet. 2015 Jan;14:76-85. doi: 10.1016/j.fsigen.2014.08.010. Epub 2014 Sep 17. PubMed PMID: 25286443.

