

# 1 **AlleleAnalyzer: a tool for personalized and allele-specific sgRNA design**

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14

## 15 **Abstract**

16 The CRISPR/Cas system is a highly specific genome editing tool capable of distinguishing alleles differing  
17 by even a single base pair. However, current tools only design sgRNAs for a reference genome, not taking  
18 into account individual variants which may generate, remove, or modify CRISPR/Cas sgRNA sites. This  
19 may cause mismatches between designed sgRNAs and the individual genome they are intended to target,  
20 leading to decreased experimental performance. Here we describe AlleleAnalyzer, a tool for designing  
21 personalized and allele-specific sgRNAs for genome editing. We leverage >2,500 human genomes to  
22 identify optimized pairs of sgRNAs that can be used for human therapeutic editing in large populations in  
23 the future.

24

25

26 **Keywords**

27

28 CRISPR, sgRNA design, genomics, genome surgery, genome editing, computational biology

29 **Background**

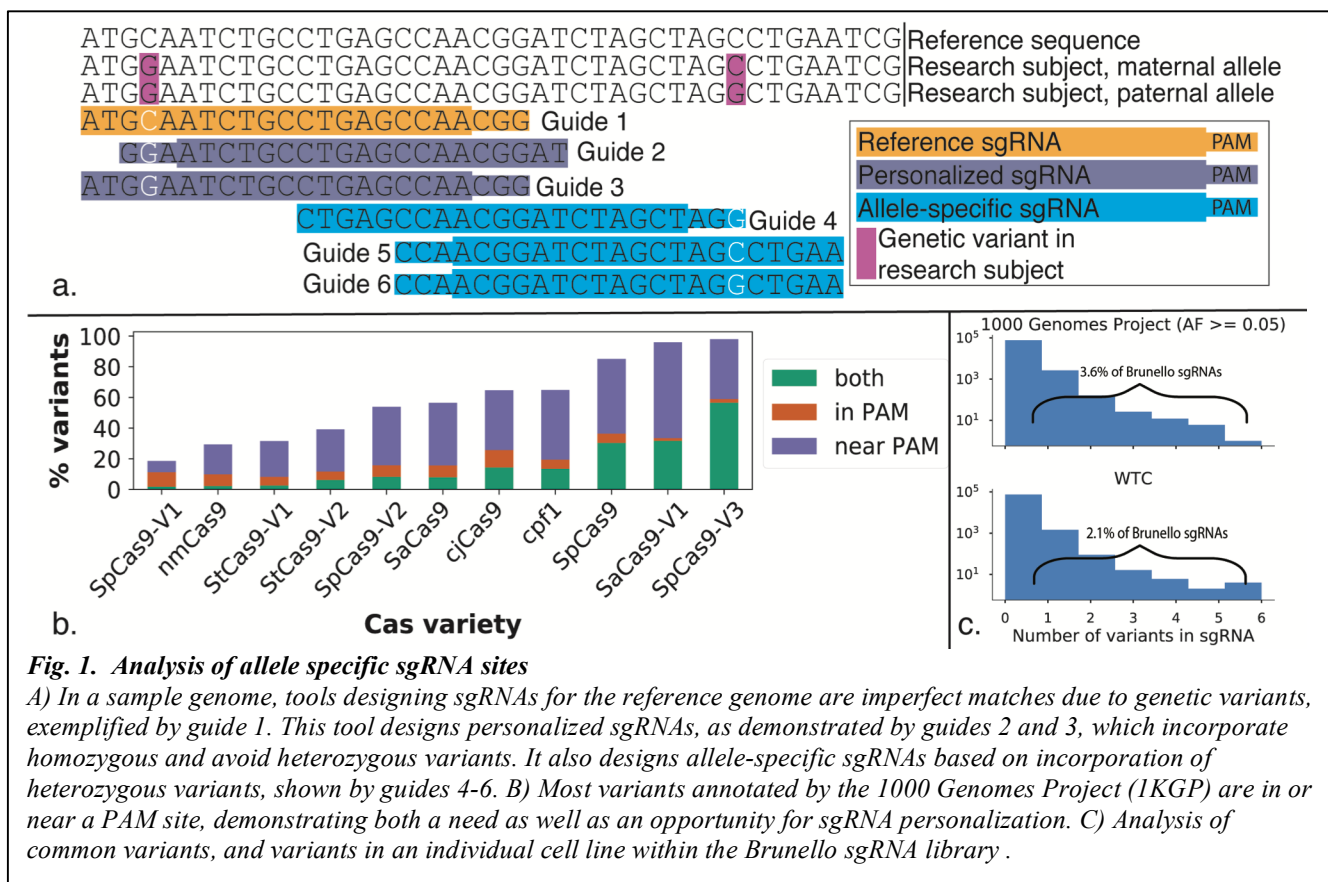
30 The CRISPR/Cas genome-editing system is highly specific, with the ability to discriminate between similar  
31 genomic sites, even alleles, based on a single nucleotide difference[1]. In order to target a genomic region  
32 with the CRISPR system, a single-guide RNA (sgRNA) must be designed that is specific to the region of  
33 interest. While current sgRNA design tools incorporate various data relating to predicted efficiency and  
34 specificity such as epigenetic marks and chromatin accessibility[2–4], in the vast majority of cases, sgRNAs  
35 are designed using reference genomes, such as the hg38 assembly for human or the GRCm38 assembly for  
36 mouse. Since sgRNAs are often used on cell lines or organisms with many nucleotide differences from the  
37 reference (e.g., on average 0.1% of a human genome[5]). Despite the finding that sgRNAs can sometimes  
38 tolerate a single basepair mismatch, these mismatches frequently negatively impact sgRNA efficiency and  
39 render imprecise the results of specificity prediction[2, 6, 7]. Furthermore, the use of CRISPR to research  
40 areas such as haploinsufficiency, genomic imprinting, and dominant negative diseases require allele-  
41 specific sgRNA design. To address these challenges, we developed AlleleAnalyzer, a software tool that  
42 designs personalized and allele-specific sgRNAs for individual genomes, identifies pairs of sgRNAs to  
43 generate excisions likely to block expression of a gene, and leverages patterns of shared variation from  
44 >2,500 human genomes to design sgRNA pairs for that will have the greatest utility in a target population.

45

46 **Results and Discussion**

47

48 Incorporating genetic variation into sgRNA design enables personalized and allele-specific CRISPR  
49 experiments. Personalized design involves accounting for variants that disrupt, generate or modify sgRNA  
50 sites in a given genome. A genetic variant can impact sgRNA sites by being located in or near a protospacer



51 adjacent motif (PAM site), potentially generating or eliminating sgRNA sites in an individual in a  
 52 heterozygous or homozygous manner. Rather than being an impediment, these variants can be incorporated  
 53 into sgRNA design, yielding personalized or allele-specific sgRNAs, depending on variant zygosity (Figure  
 54 1a). Because Cas nucleases have different PAM sequences, a variant may impact an sgRNA site for one  
 55 Cas but not another. We analyzed 11 Cas types (Supplementary Table 1) and ~81 million genome-wide  
 56 variants annotated by the 1000 Genomes Project[8] (1KGP), finding that most variants impact sgRNA sites  
 57 for at least one Cas type, even when considering only variants in PAMs, which are putatively more allele-  
 58 specific[1] (Figure 1b). The likelihood that a variant impacts an sgRNA site differs across Cas nucleases  
 59 (range: 19-98%), is positively correlated with PAM frequency in the reference genome (Pearson rho=0.9,  
 60 p=0.04), and is negatively correlated with PAM size (Pearson rho=-0.9, p=0.05). In fact, 3.6% of sgRNAs  
 61 in the widely used Brunello genome-wide CRISPR screening sgRNA library[9] contain at least one  
 62 common genetic variant (AF > 5% in the 1KGP cohort), and 2.1% of these sgRNAs contain a variant in the  
 63 individual human genome of an induced pluripotent stem cell (iPSC) line WTC, commonly used for disease

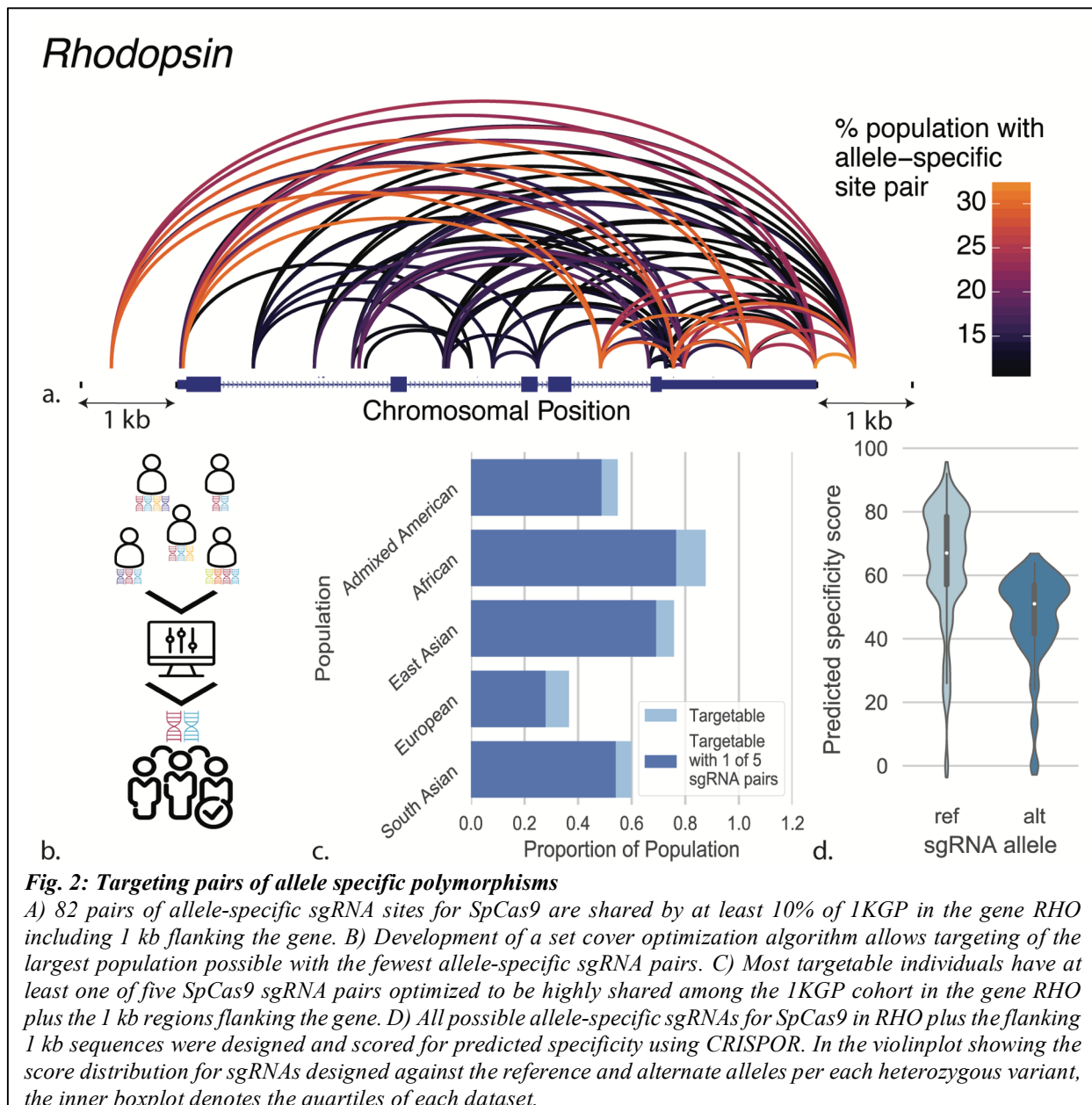
64 modeling [10] (Figure 1c), impacting ~13% of protein-coding genes in both cases. Failing to account for  
65 variants can reduce the efficacy of sgRNAs and also generate unexpected off-target effects. These results  
66 emphasize the importance of designing sgRNAs using the personal genome of the patient or cell line where  
67 they will be deployed, or at least accounting for both heterozygous and homozygous genetic variants when  
68 interpreting results using generic sgRNA libraries.

69  
70 Genetic variants are not just an impediment to sgRNA design; they can be leveraged to establish new  
71 therapeutic and research possibilities. Questions that allele-specific editing could help address include  
72 haploinsufficiency, imprinting, and allele-specific gene regulation, as well as discovery and correction of  
73 heterozygous disease variants. One promising example is genome surgery to treat dominant negative  
74 disease by excising only the disease causing copy of a gene, an approach which rescues healthy phenotypes  
75 in cell and animal models of dominant negative diseases including Huntington's disease[11] and retinitis  
76 pigmentosa[12, 13]. We assessed this strategy genome-wide by attempting to design a pair of allele-specific  
77 sgRNAs for each human protein-coding gene that could generate a genomic excision and eliminate protein  
78 production from just one allele. Given a Cas nuclease, an estimated maximum distance between the two  
79 sgRNAs on the haplotype to be excised, and allele-specific sgRNA sites, it is possible to classify genes—or  
80 other genomic elements, such as enhancers—as putatively targetable or not (Supplementary Figure 1). We  
81 use the term putatively targetable when a pair of allele-specific sgRNAs exists but has not yet been tested,  
82 because it will not always be possible to cut specifically at a site and coding exon excision will not always  
83 stop expression[14]. If we choose a maximum distance of 10 kilobases (kb) between sgRNAs, require the  
84 sgRNAs to be within the gene including introns, and consider 11 Cas varieties, the average individual from  
85 1KGP is putatively targetable for allele-specific excision at 77% of protein-coding genes. This rate is evenly  
86 distributed across chromosomes but varies by Cas nuclease and gene (Supplementary Figure 2). For genes  
87 that are not putatively targetable, additional allele-specific sgRNA sites may be found by leveraging non-  
88 coding variants up- and down-stream of the gene, or even in distal enhancers for the gene. Genome-wide,  
89 we found that by simply including the 5 kb flanking regions of each gene, we can increase the expected

90 proportion of targetable protein-coding genes per individual from 77% to 85%. We conclude that allele-  
 91 specific excision is applicable to the vast majority of genes in most human genomes.

92

93 Since some genes in a given individual do not have a pair of allele-specific sgRNAs, we asked if gene  
 94 silencing with a single allele-specific sgRNA within the coding sequence (single-guide strategy) makes  
 95 more genes excisable. We compared paired-guide and single-guide strategies for allele-specific gene  
 96 knockout in the individual human genome of the WTC iPSC line [10] and found that more than twice as



97 many genes are putatively targetable with paired guides (Supplementary Figure 3), because one or both  
98 sgRNAs can fall in introns or untranslated regions whereas single sgRNAs are limited to coding regions.  
99 Genes that are putatively targetable with a single- and not paired-guide approach tend to have less than two  
100 heterozygous variants in the gene, indicating lack of multiple variants as the primary reason a paired-guide  
101 strategy fails. These genes likely could be putatively targetable with a paired-guide strategy by  
102 incorporating flanking, promoter, or other regulatory regions. We therefore recommend paired-guides for  
103 allele-specific gene excision.

104  
105 Genome editing sgRNAs do not need to be designed one genome at a time. Variants that impact sgRNA  
106 sites are often shared among large proportions of the individuals within and sometimes between populations  
107 due to haplotype structure. Allele sharing varies by population and locus, as individuals with common  
108 ancestry will share haplotypes that harbor specific sets of variants. We therefore developed an algorithm to  
109 identify allele-specific sgRNA guide pairs for a given gene that cover the maximum number of individuals  
110 in a population; these have the broadest therapeutic potential, similar to designing a drug to treat as many  
111 people as possible. Specifically, our method seeks to cover the most people with the fewest sgRNA pairs  
112 using their shared heterozygous variants; this is similar to the set cover problem in that the algorithm  
113 identifies an optimal combination rather than simply selecting most shared sgRNA pairs, which could  
114 disproportionately favor one group over another [15]. Our algorithm generates optimized pairs of sgRNAs  
115 that can be used to study or treat genetic diseases in large groups, potentially eliminating the need to develop  
116 new sgRNA pairs for each patient or cell line, with practical implications for the development of genome  
117 surgery as a field. Our algorithm can also be used to identify sgRNA pair combinations applicable to a  
118 custom cohort, enabling researchers to design guides that are maximally shared among multiple cell lines,  
119 for example, which would improve experimental efficiency.

120  
121 As a case study, we investigated the feasibility of excising one allele of exon 1 of *RHO*, which can cause  
122 dominant negative macular dystrophy[13]. Considering the gene plus 1 kb of flanking sequence on either

123 side, there are 82 pairs of allele-specific sgRNA sites for SpCas9 that are shared by >10% of all 1KGP  
124 individuals, with the number and composition of these pairs varying across 1KGP populations (Figure 2a,  
125 Supplementary Figure 4). We sought to identify an optimal combination of five allele-specific sgRNA pairs  
126 to target the majority of the 1KGP cohort (Figure 2b). We found that five allele-specific sgRNA pairs could  
127 putatively excise one allele of *RHO* while leaving the other allele intact in ~88% of 1KGP individuals with  
128 at least two variants, or 57% of the overall 1KGP population (Figure 2c). We also demonstrated how  
129 avoiding heterozygous variants and incorporating homozygous variants enables personalized sgRNA  
130 design in the *RHO* locus for the WTC genome for many Cas varieties, including SpCas9, SaCas9 and cpf1  
131 (Cas12a) (Supplementary Figure 5, Supplementary Tables 2 and 3). The dominant negative disease gene  
132 *RHO* clearly demonstrates the power of using genetic variation in sgRNA design.

133  
134 We incorporated these methods into AlleleAnalyzer, an open-source software tool (Supplementary Figure  
135 6). This tool designs personalized and allele-specific sgRNAs for unique individuals and cohorts, given  
136 their genetic variants, and optimizes sgRNA pairs to cover many individuals based on shared variants. To  
137 our knowledge, this is the first computational resource that designs personalized and allele-specific CRISPR  
138 sgRNAs, thus expanding and building upon the existing repertoire of sgRNA design tools (Supplementary  
139 Table 4). We integrated the specificity scoring capabilities of CRISPOR[4] to enable users to stratify guides  
140 by that metric as desired (Figure 2d). The AlleleAnalyzer toolkit and tutorials are available along with the  
141 database of annotated 1KGP variants (Supplementary Table 5) at  
142 <https://github.com/keoughkath/AlleleAnalyzer>.

143  
144 **Conclusions**  
145 The genetic variation aware sgRNA design tool AlleleAnalyzer is an important step towards effective  
146 deployment of CRISPR-based technologies in diverse genomes, including but not limited to research and  
147 therapeutic development for once incurable dominant negative diseases.

148

149 **Methods**

150 *PAM occurrence in the human reference genome*

151 **PAM frequency**

152 The AlleleAnalyzer tool includes a script enabling scanning of a reference genome fasta file for existing  
153 PAM sites. We used this to identify PAM sites for 11 Cas types (Supplementary Table 1) in the reference  
154 human genomes hg19 and hg38.

155 **PAM size**

156 PAM sizes were equated as the sum of non-N (A, C, G or T) bases in a PAM site. Thus “NGG” for SpCas9  
157 would have size 2, and “NNGRRT” for SaCas9 would have size 4.

158 *AlleleAnalyzer analysis of the 1000 Genomes cohort*

159 **Annotation of variants**

160 Genetic variants were determined to generate or destroy an allele-specific sgRNA site if they were proximal  
161 to or in a PAM site (Figure 1a). Sufficient proximity to a PAM site was defined for this study as 20 base  
162 pairs based on the common length of sgRNA recognition sequences. For all Cas varieties this was the 20  
163 base pairs 5’ of the PAM, except for cpfl1 (Cas12a) for which it was 3’ of the PAM. The sgRNA design  
164 tools that are part of AlleleAnalyzer allow different user-defined sgRNA lengths and addition of Cas  
165 enzymes and PAMs. There is evidence to suggest that genetic variants that generate or destroy a PAM are  
166 more likely to lead to allele-specific Cas activity compared to those in the seed sequence<sup>1</sup>; AlleleAnalyzer  
167 thus provides options to differentiate between CRISPR sites in a PAM site versus the sgRNA recognition  
168 sequence. All variants genome-wide were annotated for the 1KGP cohort for reference genomes hg19 and  
169 hg38 and are available for querying; an example subset of these data for the first 100 variants annotated by  
170 1KGP on chromosome 1 in reference genome hg19 is available in Supplementary Table 5.



## 171 **Generation of gene set**

172 The gene set analyzed was compiled using the canonical transcripts for RefSeq gene annotations for human  
173 reference genome hg19 and hg38 downloaded using the UCSC table browser[16], and filtered for genes  
174 with at least one coding exon. When non-protein-coding genes were excluded, 15,199 genes were evaluated  
175 for hg19, and 16,143 for hg38. Values reported in the text are for hg19 unless stated otherwise, but analyses  
176 were conducted for both reference genomes with similar results.

## 177 **Allele-specific putative gene targetability genome-wide**

178 Putative allele-specific targetability of a gene is defined here as whether a gene contains a pair of allele-  
179 specific sgRNA sites for at least one of the 11 Cas enzymes evaluated that are less than 10 kb apart on the  
180 same haplotype in an individual that will disrupt a coding exon (Supplementary Figure 1). This metric was  
181 calculated for each protein-coding gene for all 2,504 1KGP individuals.

## 182 **Set cover analysis**

183 In order to determine optimal pairs of sgRNAs to cover large groups of people in a particular gene, we  
184 applied set cover optimization which we implemented using the Python package PuLP[17]. The aim was  
185 to maximize the number of individuals from the 1KGP for whom a user-supplied maximum number of  
186 sgRNA pairs would putatively target a given gene. This script can also be used to determine a minimum  
187 percentage of people to be covered by a set of sgRNA pairs.

## 188 ***WTC sequencing***

189 The genome for the iPSC line WTC[10] was sequenced by the Allen Cell Science Institute. Analysis and  
190 variant calls in the reference genome hg19 were done according to GATK version 3.7 best practices[18]  
191 and phased using Beagle version 4.1 with default settings[19].

192 ***WTC targetability analysis***

193 Variant annotation procedures were the same as in the 1KGP analysis. The same genes lists used in the  
194 1KGP analysis were analyzed in WTC, except when specified in the text, for the cases of 1 kb flanking the  
195 gene *RHO*, or when analyzing targetability for all genes + 5 kb flanking vs. genic region only.

196 ***Packages used***

197 **Python**

198 Docopt was used for handling of command-line arguments. Pandas[20] version 0.21.0 and NumPy[21]  
199 version 1.13.3 and elements of the standard Python distribution sys, os, and regex were used for multiple  
200 aspects of data analysis. PuLP[17] version 1.6.8 was used for set cover analysis. PyTables[22] was used for  
201 data management. Biopython[23] and pyfaidx[24] were used for Fasta processing. Scripts from  
202 CRISPOR[4] were integrated into AlleleAnalyzer to facilitate specificity scoring of sgRNAs.

203 **R**

204 Packages used to generate arcplots included viridis version 0.5.1, viridisLite version 0.3.0, igraph version  
205 1.1.2, ggraph version 1.0.0, ggplot2 version 2.2.1, reshape2 version 1.4.3, dplyr version 0.7.4, tidyr version  
206 0.7.2, and readr version 1.1.1.

207 **Bioinformatics**

208 Bcftools versions 1.5 and 1.6 were used to manipulate VCF and BCF files.

209 ***Scripts***

210 Scripts were written in Python version 3.6.1, R version 3.3.2 and Bash version 3.2.57.

211 ***Data Availability***

212 1KGP phase 3 data were downloaded from the 1KGP website (<http://www.internationalgenome.org/>). The  
213 reference hg19 and hg38 genome data were downloaded from the UCSC genome browser. The 1KGP  
214 analysis dataset has been made available for public access online at  
215 ([http://lighthouse.ucsf.edu/public\\_files\\_no\\_password/excisionFinderData\\_public/1kgp\\_dat/](http://lighthouse.ucsf.edu/public_files_no_password/excisionFinderData_public/1kgp_dat/)).

216 ***Code Availability***

217 All data processing and analysis scripts as well as the sgRNA design tool are located at  
218 [github.com/keoughkath/AlleleAnalyzer](https://github.com/keoughkath/AlleleAnalyzer).

219 **List of Abbreviations**

220 sgRNA: single-guide RNA

221 PAM site: protospacer adjacent motif site

222 1KGP: 1000 Genomes Project

223 kb: kilobases (1000 genomic basepairs)

224 iPSC: induced pluripotent stem cell

225 **Declarations**

226 ***Ethics approval and consent to participate***

227

228 Not applicable.

229

230 ***Consent for publication***

231 Not applicable.

232

### 233 *Availability of Data and Material*

234

235 All data processing and analysis scripts as well as the sgRNA design tool are located at  
236 [github.com/keoughkath/AlleleAnalyzer](http://github.com/keoughkath/AlleleAnalyzer). 1KGP phase 3 data were downloaded from the 1KGP website  
237 (<http://www.internationalgenome.org/>). The reference hg19 and hg38 genome data were downloaded from  
238 the UCSC genome browser. The 1KGP analysis dataset has been made available for public access online  
239 at ([http://lighthouse.ucsf.edu/public\\_files\\_no\\_password/excisionFinderData\\_public/1kgp\\_dat/](http://lighthouse.ucsf.edu/public_files_no_password/excisionFinderData_public/1kgp_dat/)). WTC  
240 whole-genome sequencing data is made available by the Allen Institute at  
241 (<https://www.allencell.org/genomics.html>).

### 242 *Competing Interests*

243 B.R.C. is a founder of Tenaya Therapeutics, a company focused on finding treatments for heart failure,  
244 including the use of CRISPR interference to interrogate genetic cardiomyopathies. B.R.C. and K.S.P. hold  
245 equity in Tenaya, and Tenaya provides research support for heart failure related research to B.R.C. and K.S.P.  
246

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248

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## 253 ***Authors' Contributions***

254 K.C.K, S.W., B.R.C., and K.S.P. conceived the project. K.C.K, S.W., S.L., B.R.C., and K.S.P. designed the  
255 experiments, K.C.K, S.L., M.P.O., B.R.C., and K.S.P. analyzed data. K.C.K, B.R.C., and K.S.P. wrote the  
256 paper with editing from all other authors.

## 257 **Acknowledgements**

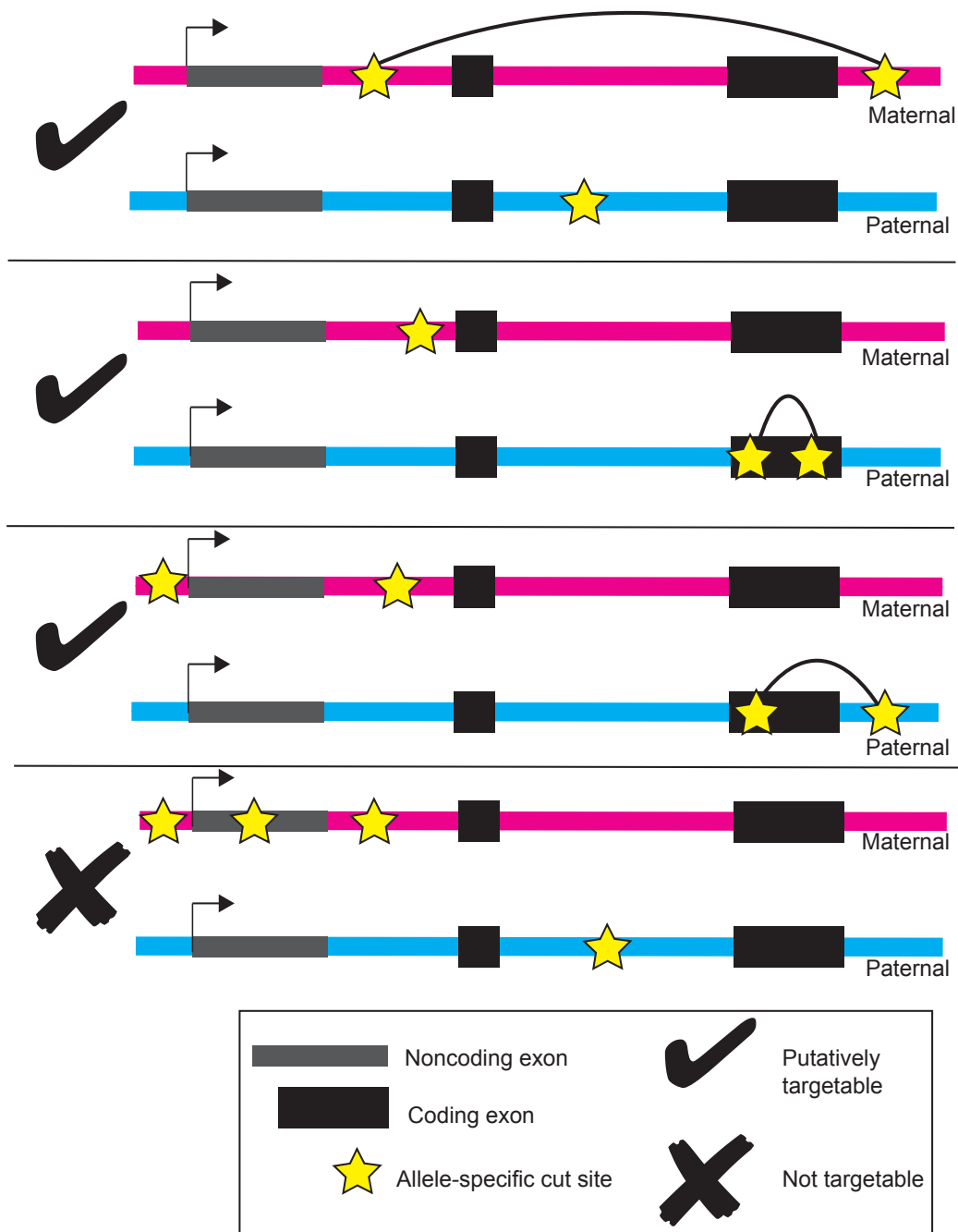
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261 CRISPOR.

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320 **Supplementary Figure 1**

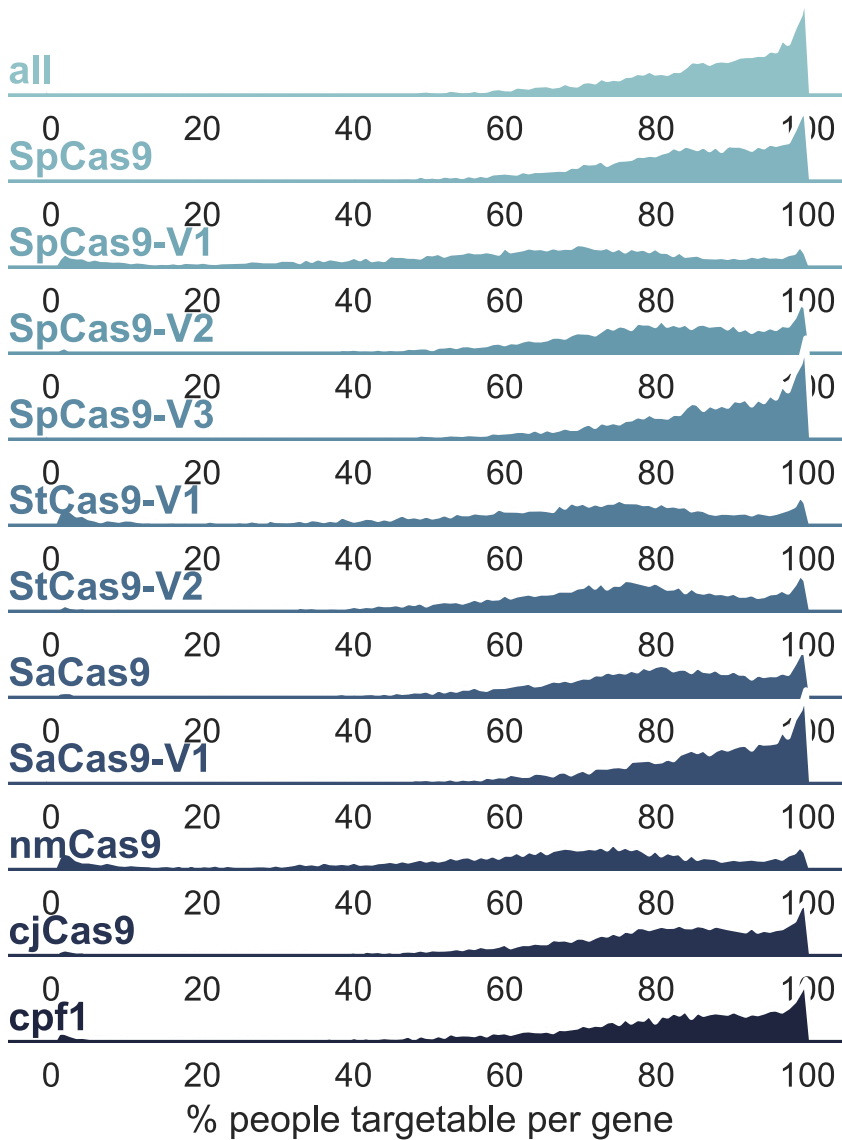
321 A pair of allele-specific sgRNA sites is defined as putatively targetable if their predicted excision will  
322 disrupt at least one protein-coding exon.

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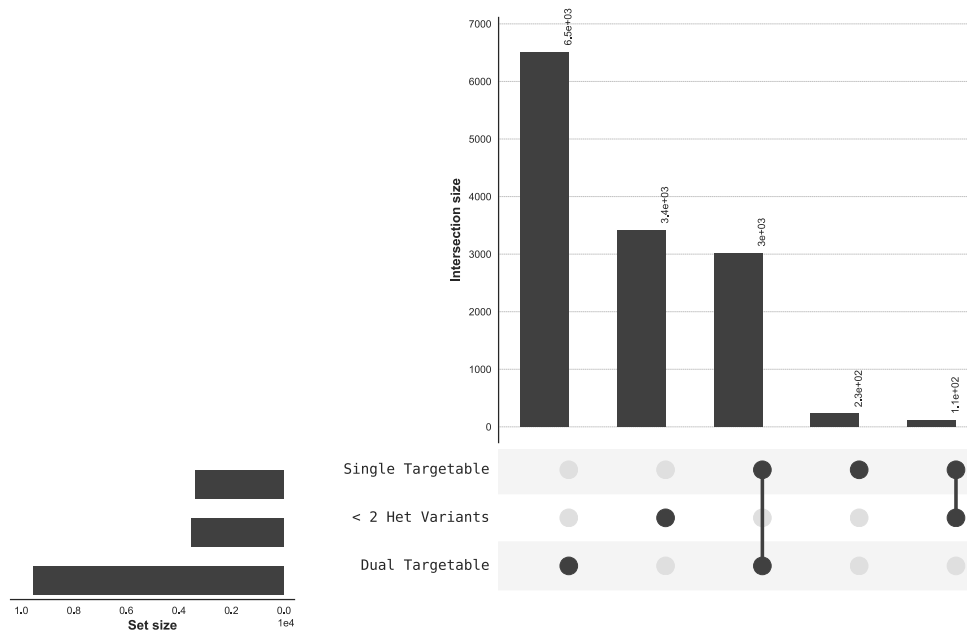
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329

### 330 **Supplementary Figure 2**

331 This faceted density plot shows the percentage of putatively targetable 1KGP individuals (2,504 total individuals) per  
332 protein-coding gene for 11 types of Cas nuclease.



### 333 **Supplementary Figure 3**

334 Many more genes are targetable in the genome of WTC with a paired (dual)- as opposed to single-guide  
335 strategy. The number of variants in a gene is influential in determining targetability. Many genes that are  
336 not dual- or single-guide targetable have very few variants, and the genes that are only targetable with a  
337 single-guide approach compared to a dual-guide approach also tend to have fewer variants. All 11 Cas  
338 varieties are considered in this analysis.

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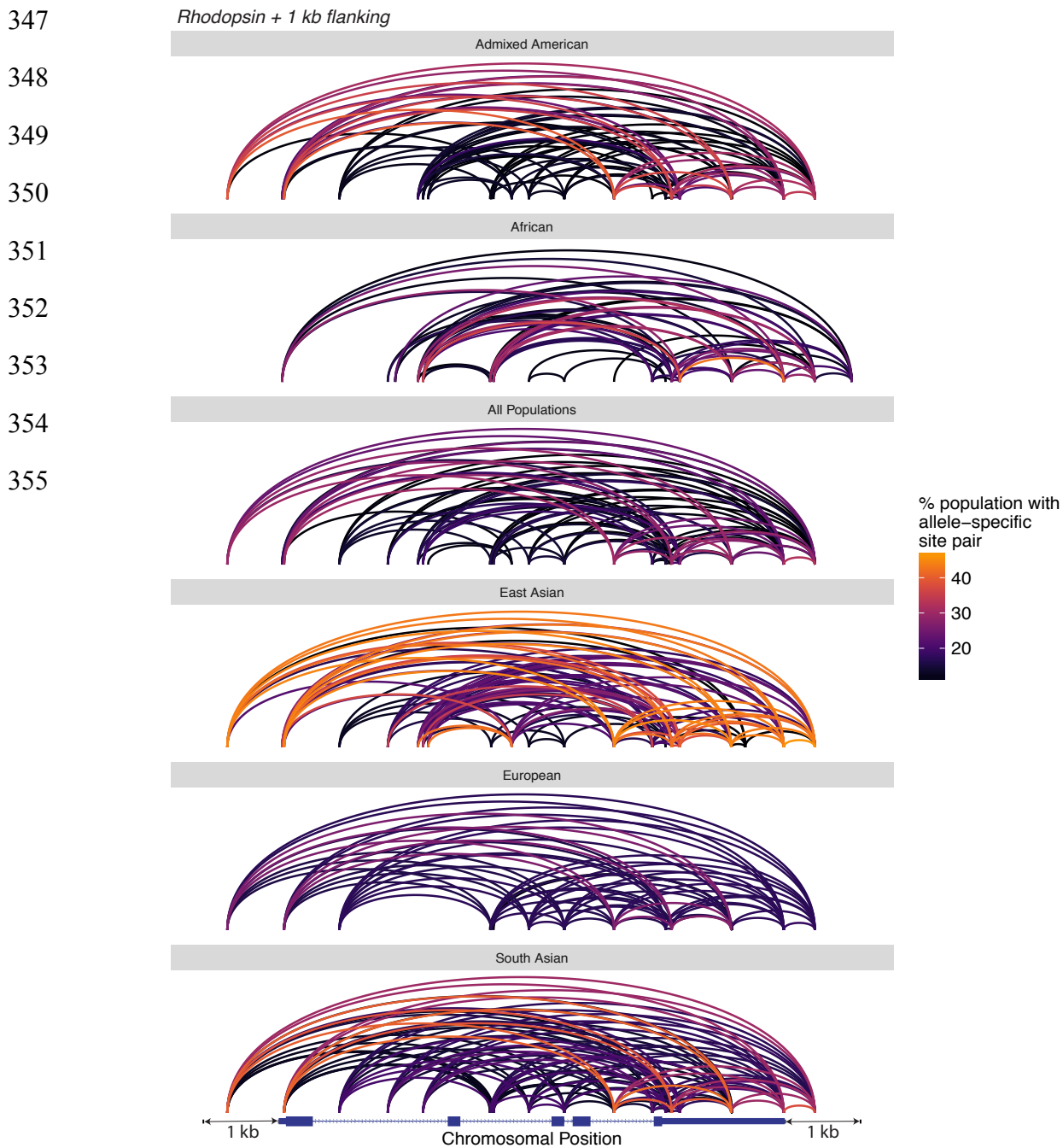
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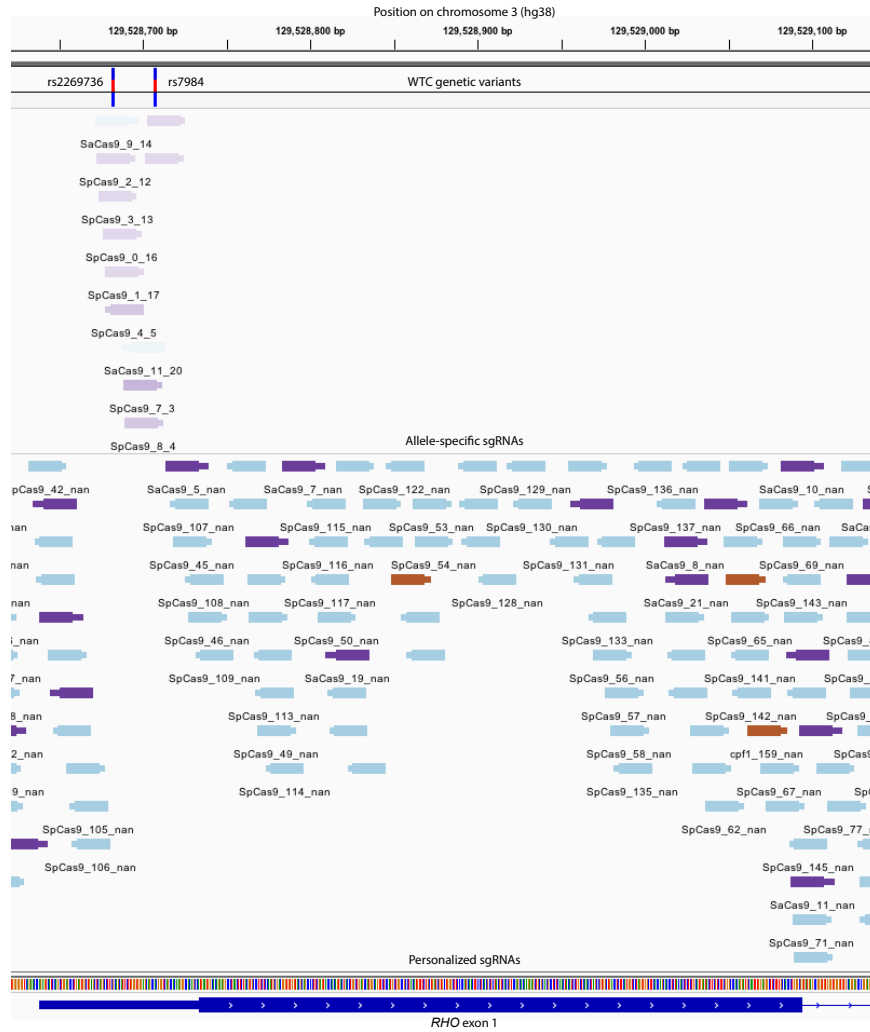
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356 **Supplementary Figure 4**

357 Shared pairs of sgRNAs per locus vary by population. We show allele-specific sgRNA site pairs shared by  
358 at least 10% of each population for SpCas9 in the gene *RHO* plus the 1 kb flanking regions in the five super-  
359 populations in the 1KGP as well as the overall 1KGP cohort.

360



Nucleases evaluated: SpCas9, SaCas9, cpf1 (Cas12a)

361

## 362 Supplementary Figure 5

363 Integrative Genomics Viewer track view of allele-specific (lavender, upper track) and personalized (multi-

364 colored, middle track) sgRNAs for SpCas9, SaCas9 and cpf1 (Cas12a) in the gene *RHO* plus 1 kb flanking

365 in WTC. Allele-specific guides are shaded according to position of the variant in the guide, with variants

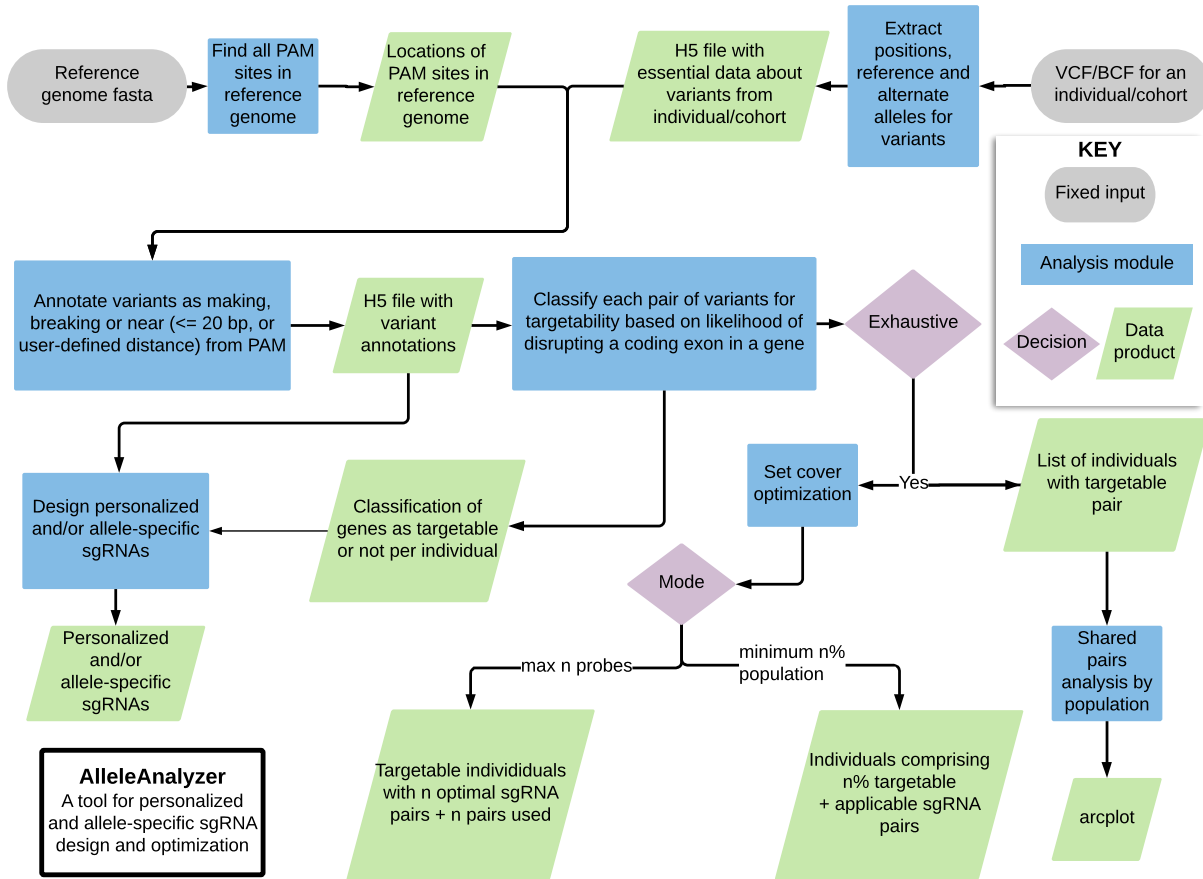
366 closer to the PAM being darker based on their putative greater specificity. The track labeled “WTC genetic

367 variants” (top) denotes genetic variants in WTC in this locus, of which there are only heterozygous variants.

368 The bottom track shows the RefSeq annotation for the first exon of this gene in hg38.

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372 **Supplementary Figure 6**

373 Flowchart for the AlleleAnalyzer software tool.

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Common name(s)	Abbreviation	PAM	Properties
SpCas9	SpCas9	NGG	<i>Streptococcus pyogenes</i> (Sp) Cas9., most widely used version with dozens of variants using same PAM, e.g. eSpCas9, SpCas9-HF1, eSpCas9 1.1 and more (Jinek et al. 2012)
SpCas9 VRER Variant	SpCas9-V1	NGCG	Version of SpCas9 with alternative targeting range (Kleinstiver et al. 2015)
SpCas9 EQR Variant	SpCas9-V2	NGAG	Version of SpCas9 with alternative targeting range (Kleinstiver et al. 2015)
SpCas9 VQR Variant	SpCas9-V3	NGAN or NGNG	Version of SpCas9 with wider targeting range (Kleinstiver et al. 2015)
SaCas9	SaCas9	NNGRRT	<i>Staphylococcus aureus</i> (Sa) Cas9. Small relative to SpCas9, (Horvath et al. 2008, Jiang et al. 2013)
SaCas9 KKH Variant	SaCas9-V1	NNNRT	Version of SaCas9 with 2 to 4-fold increased targeting range relative of SaCas9 (Kleinstiver et al. 2015)
nmCas9	nmCas9	NNNNGATT	<i>Neisseria meningitidis</i> (Nm) Cas9, with different PAM site (Hou et al. 2013)
cpf1	cpf1	TTTN	Multiple variations, notably opposite orientation system and sticky-end cut rather than blunt. Multiple species exist, including from <i>Acidaminococcus</i> and <i>Lachnospiraceae</i> . (Zetsche et al. 2015)
StCas9 1	StCas9-V1	NNAGAA	<i>Streptococcus thermophilus</i> (St) Cas9. Smaller relative of SpCas9. Increased specificity. (Kleinstiver et al. 2015, Muller et al. 2016)
StCas9 2	StCas9-V2	NGGNG	<i>Streptococcus thermophilus</i> (St) Cas9. Smaller relative of SpCas9. Increased specificity. (Muller et al. 2016)
cjCas9	cjCas9	NNNNACA	<i>Campylobacter jejuni</i> Cas9. Smallest Cas9 ortholog to date, easy to package (Kim et al. 2017)

397 **Supplementary Table 1**

398 11 types of Cas enzyme were evaluated, each of which has a distinct PAM site.

399 **Supplementary Table 2**

400

401 All possible allele-specific sgRNAs for SpCas9, SaCas9 and cpf1 (Cas12a) in the region surrounding the

402 first exon of *RHO* WTC (Supplementary Figure 6).

403 **Supplementary Table 3**

404 All possible personalized sgRNAs for SpCas9, SaCas9 and cpf1 (Cas12a) in the region surrounding the  
 405 first exon of *RHO* WTC (Supplementary Figure 6). WTC has no homozygous variants in this region, thus  
 406 allele frequency and variant-related columns are blank. However, the sgRNAs are designed to avoid the 9  
 407 heterozygous variants that WTC has in this region.

	Personalized sgRNA design	Allele-specific sgRNA design	Supports any genome	Paired sgRNA design	Optimizes pairs of sgRNAs to maximize coverage in a cohort	Single or multi-locus design	Multiple Cas varieties	Ability to add novel Cas enzymes	Off-target scoring
AlleleAnalyzer	yes	yes	yes	yes	yes	yes	yes	yes	yes
CRISPOR (Haeussler et al. 2016)	no	no	yes	no	no	yes	yes	no	yes
GuideScan (Perez et al. 2017)	no	no	no	yes	no	yes	yes	no	yes
E-CRISP (Heigwer et al. 2014)	no	no	no	yes	no	yes	no	no	yes
MIT design tool (Hsu et al. 2013)	no	no	no	no	no	yes	no	no	yes
CRISPRscan (Moreno-Mateos et al. 2015)	no	no	no	no	no	no	yes	no	yes
FlashFry (McKenna & Shendure, 2018)	no	no	yes	no	no	yes	yes	no	yes

408

409 **Supplementary Table 4**

410 Comparison of AlleleAnalyzer features with other commonly used CRISPR sgRNA design tools.

411

412 **Supplementary Table 5**

413 An example subset of variant annotations for the first 100 variants on chromosome 1 from 1KGP.

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