

1 Towards a new standard in genomic 2 data privacy: a realization of owner- 3 governance

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12
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16 Abstract

17 With the rapid developments in sequencing technologies, individuals now have
18 unprecedented access to their genomic data. However, existing data management systems
19 or protocols are inadequate for protecting privacy, limiting individuals' control over their
20 genomic information, hindering data sharing, and posing a challenge for biomedical
21 research. To fill the gap, an owner-governed system that fulfills owner authority, lifecycle
22 data encryption, and verifiability at the same time is prompted. In this paper, we realized
23 Govername, an owner-governed data management system designed to empower individuals
24 with absolute control over their genomic data during data sharing. Govername uses a
25 blockchain to manage all transactions and permissions, enabling data owners with dynamic
26 permission management and to be fully informed about every data usage. It uses
27 homomorphic encryption and zero-knowledge proofs to enable genomic data storage and
28 computation in an encrypted and verifiable form for its whole lifecycle. Govername supports
29 genomic analysis tasks, including individual variant query, cohort study, GWAS analysis, and
30 forensics. Query of a variant's genotype distribution among 2,504 1kGP individuals in
31 Govername can be efficiently completed in under 18 hours on an ordinary server.
32 Govername is an open-source project available at <https://github.com/HKU-BAL/Governome>.

34 Introduction

35 The advent of affordable advanced sequencing technologies has empowered individuals to
36 explore their health condition through personal genomics, highlighting the critical role
37 genomics plays in modern healthcare ¹. With increased accessibility, data privacy and
38 security have become an emerging issue when managing personal genomic data. With
39 limitations in storage and analytical capabilities, many individuals opt for third-party services

40 to host and analyze their genomic data. These services offer medical insights and analyses
41 related to ancestry and disease susceptibility, expanding the utility of genomic data beyond
42 the clinical setting.

43
44 Despite the benefits, relying on third-party services introduces inherent privacy risks. Users
45 often compromise control over their data by agreeing to terms with limited choices. This
46 leaves the data vulnerable to potential mishandling or misuse, particularly in unregulated
47 contexts. Instances have been documented in which commercial companies share genomic
48 data with pharmaceutical firms in exchange for financial incentives, underscoring the
49 importance of ethical practices related to data security ². Such data mismanagement can
50 have immediate consequences. For example, individuals with high-risk genetic markers are
51 denied life insurance coverage due to undisclosed genomic data usage ³. Moreover, when
52 using third-party services, ensuring "The Right to be Forgotten" in the General Data
53 Protection Regulation (GDPR) ⁴, specifically the revocation of data access, is challenging.
54 The revocation process typically relies on users submitting requests to third parties, who
55 must then comply with relevant regulations. This dependency on third-party compliance
56 makes it difficult to ensure that data access revocation can be executed without undue
57 delay, let alone achieve instant data access control.

58
59 The issue of genomic data privacy quickly caught the attention of the academic community,
60 resulting in the development of various methods to protect data. Existing human genomic
61 databases ⁵⁻⁷ host research-funded genomic data, and they achieve data privacy by
62 providing access only to successful applicants. Another approach is to provide a unified API
63 for cross-institution genomic data sharing, thereby enabling a centralized gateway with
64 security protocol. Beacon Service, by GA4GH ⁸, was an early attempt at federated data
65 sharing. It aims to achieve collaboration across databases through a distributed storage and
66 sharing network. Despite its intent to facilitate collaboration, the potential for reidentification ⁹
67 through query analysis remains a critical privacy issue.

68
69 Cryptogenomics, which involves applying cryptographic methods to genomic data, is a
70 promising solution for genomic data privacy. Early efforts focused on privacy-preserving data
71 sharing and computation among institutions (also called data custodians). These methods
72 are typically designed for specific genomics analysis tasks, such as cross-institutional single-
73 gene disease diagnosis query ¹⁰, GWAS ^{11,12} and genetic imputation ¹³. These task-specific
74 protocols by different institutions vary in specializations and capabilities, while none offers
75 personal genome data owner timely and full control of their own data.

76
77 Blockchain technology ¹⁴ offers a new insight to the field of cryptogenomics. Blockchain is a
78 distributed ledger technology that enables multiple participants to engage in secure
79 transactions and information sharing transparently without a central authority, which naturally
80 aligns with the requirements of personal genome data owners retaining full authority over
81 their genomic data without intermediaries as data custodians ¹⁵. Therefore, starting in 2018,
82 a well-known genomics security contest named iDASH ¹⁶ extended blockchain to one of its
83 security computing tracks for the task of recording patients' data sharing consents. There
84 have been attempts ¹⁷ to store and share genomic data directly using blockchain. While it
85 ensures the security and immutability of transactions, the privacy of information stored on-
86 chain is lost since any participant with read-access to the system can directly access the raw
87 genomic data. Another attempt introduced a citizen-centered method ¹⁸ that involved both

88 secure computation and a blockchain-based system. However, it supports only simple
89 genomics analysis tasks because only addition operation is supported in its secure
90 computation design, making it impractical for real-life genomics analysis tasks. It also lacks a
91 measurement to avoid data owners and computing parities from providing false information,
92 which is inevitable as the number of participants grows.

93
94 We consider that the full-fulfillment of owner-governance is the next step of cryptogenomics.
95 Owner-governance implies three properties throughout the entire lifecycle of genomic data:
96 1) the data owner retains full authority of her data, 2) the genomic data remains encrypted,
97 and 3) the integrity of both the genomic data and the computation results is algorithmically
98 guaranteed. Practical solutions are urged for a comprehensive owner-governed genomic
99 data management system that should at least include features including user anonymity,
100 dynamic data access control, record audibility, secure data analysis¹⁹, and verifiable
101 analysis results. In existing human genomic databases^{5-7,9}, data access revocation is
102 difficult if not undoable once the data has been shared and kept another copy. Queries about
103 data usage logs and permission control are also entirely reliant on the credibility of the data
104 custodian. Thus, establishing a comprehensive system for owner-governed genomic data
105 management is imperative for addressing privacy concerns and empowering individuals in
106 the genomic data landscape.

107
108 In this paper, we explored the pathways to achieving the three properties of owner-
109 governance, namely Owner Authority, Lifecycle Data Encryption, and Verifiability. We
110 developed Govername, a realization of owner-governance that fulfills all three properties.
111 Govername utilizes a blockchain to manage all transactions and permissions, enabling data
112 owners with dynamic permission management and to be fully informed about all data usage.
113 It uses homomorphic encryption and zero-knowledge proofs to enable genomic data storage
114 and computation in an encrypted and verifiable form in its complete lifecycle. Data owners
115 can share or unshare their genome in the system instantly. Querying entities can conduct
116 analyses, including individual variant queries, cohort studies, GWAS analyses, and
117 forensics. We benchmarked Govername for different applications and found that querying
118 the population genotype distribution of a random SNP (Single Nucleotide Polymorphism)
119 over 2,504 1kGP²⁰ individuals can be efficiently completed in under 18 hours on an ordinary
120 server. Our experiments demonstrated that Govername can be applied to different genomic
121 data management scenarios at scale. Govername is open-source and available at
122 <https://github.com/HKU-BAL/Govername>. To our best knowledge, Govername is the first
123 realization of a secure, transparent, decentralized data management system that enables
124 owner-governed genomic data management. We hope that Govername can set a new
125 standard for privacy protection and data sharing in the personal genome era, and in turn
126 benefit personalized medicine and facilitate population genetics researcher at a larger scale.
127

128 Results

129 Overview

130 We defined three properties that lead to the full-fulfillment of owner-governance in a genomic
131 data management system: Owner Authority, Lifecycle Data Encryption, and Verifiability. We

132 developed Governone that fulfilled owner-governance. Governone enables data owners to
133 have 24/7 instantaneous control of their genomic data with full transparency. No plaintext
134 information is stored or generated in the system to eradicate any sort of data leakage. Data
135 integrity and computation result authenticity are algorithmically ensured. Governone
136 supports different genomic tasks, including variant query, cohort study, GWAS analysis, and
137 forensics. We demonstrated Governone's performance with all variants of the 2,504 1kGP
138 samples, suggesting its robustness when managing large-scale human genome projects and
139 its potential to be scaled-up to managing millions of samples.
140

141 The three properties of owner-governance

142 We consider a genomic data management system is capable of owner-governance if it
143 simultaneously has the following three properties:

144

- 145 1) **Owner Authority (OA):** Owners have absolute and instantaneous control over
146 their owned genomic data. At any given time, data owners should be able to
147 modify the access permissions of their genomic data in the system, including
148 revoking data access entirely for any usage. OA also includes data owners'
149 access to complete data usage logs that are guaranteed to be authentic.

150

- 151 2) **Lifecycle Data Encryption (LDE):** Data must remain encrypted throughout its
152 lifecycle in the system, ensuring that it is never decrypted or accessed in raw
153 form to protect data security. Encryption should be comprehensively applied to
154 users' raw data or intermediate computation results in the stage of storage,
155 exchange, and computation. No party, including the data owner, should have
156 direct access to raw information except for the final result provided by the system.

157

- 158 3) **Verifiability (VER):** Verifiability includes data integrity verifiability and
159 computation process verifiability. Data integrity verifiability refers to the querying
160 entities who initiate a query analysis in the system are able to verify whether the
161 genomic data is free from tampering. Computation process verifiability requires
162 the system to be able to provide evidence for the correctness of the results of any
163 computing process.

164

165 Necessity of the three properties

166 OA is the core principle of owner-governance, which implies around-the-clock intermediary-
167 free revocation and traceability. Intermediary-free revocation means that the data owners
168 can break away from their previous commitments freely and at any time without any
169 intermediary - they can be the ultimate decision-maker regarding data access or their own
170 data. Traceability means data owners are fully informed, addressing information asymmetry
171 challenges and enhancing control. The combination of decision-making and the right to be
172 informed forms the basis of data owner's authority over their own data.

173

174 LDE is an inevitable requirement for ensuring data security in an owner-governed system.
175 Unless proven otherwise, any disclosure of raw data, even to data owners, will result in

176 potential risks such as information theft and storage device loss, which can have an
177 irreversible impact on data privacy. On the other hand, any party that acquires access to any
178 raw data or intermediate results in plaintext means a deviation from OA since the party can
179 maintain a copy with or without permission, which undermines data owner's right to decision-
180 making.

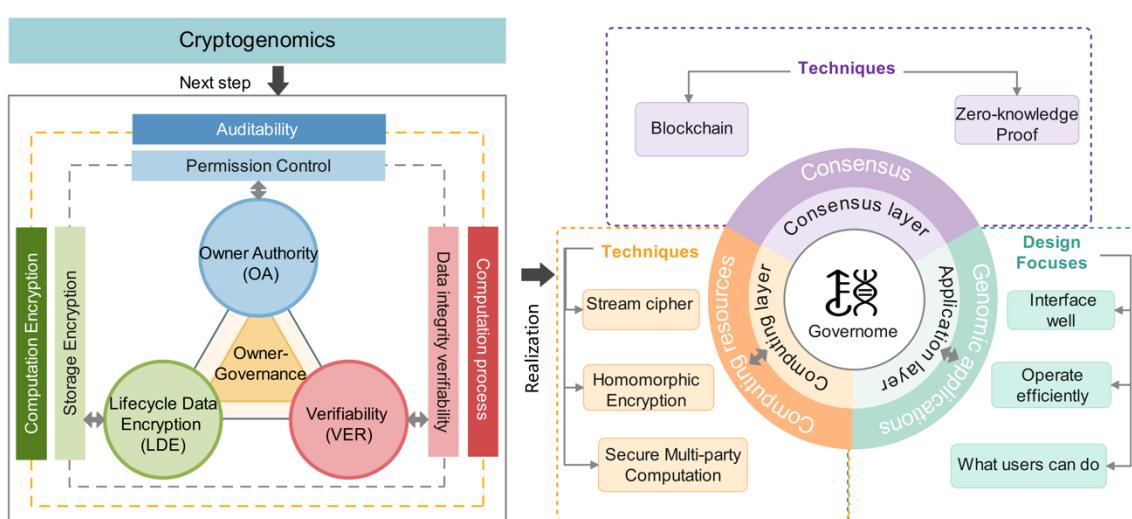
181
182 VER ensures that the querying entities can always achieve the correct result, which is the
183 foundation of usability. It prevents malicious participants from providing false information that
184 could fake an identity or void research. The use of a blockchain implies crowdsourced data
185 storage and computing. Hence, without a proper mechanism, a dishonest data provider or
186 computing provider might act maliciously and cause permanent damage to the usability of
187 the system. The principle of enabling VER is to trust no one and use mathematical and
188 cryptographic tools to enforce data and computation integrity.

189
190 Without OA, data owners would effectively lose control over their genomic data. Without
191 LDE, the genomic data within the system would face inevitable privacy risks when being
192 used. Without VER, the system would lose its trustworthiness, and usability in the end.
193 Therefore, as the next step of cryptogenomics, the three properties OA, LDE, and VER are
194 integral.

195

196 Governone realizes owner-governance

197 We developed Governone that fulfills the three properties simultaneously. To our best
198 knowledge, it is the first realization of an owner-governance genomic data management
199 system. As shown in Figure 1, Governone includes three layers: 1) a consensus layer to
200 manage agreements among users; 2) a computing layer to manage the different forms of
201 genomic data at various stages, including data storage, exchange, and analysis; and 3) an
202 application layer as an interface for users to interact with the consensus layer and computing
203 layer. The functionality of Governone is built upon the synergy of the three layers. Details
204 about the techniques and design focuses at the three layers are shown in the 'Feasible
205 approaches to fulfill the three properties of owner-governance' subsection in Methods.
206

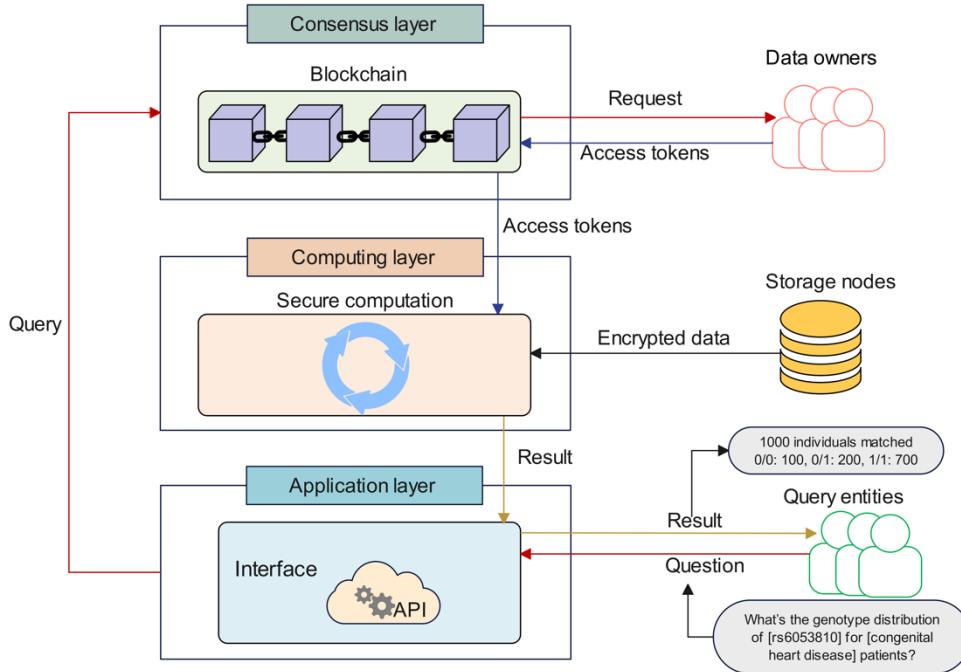


207

208 Figure 1. An overview of owner-governance and its realization, Govername. Owner-governance
209 requires three properties, 1) Owner Authority - owners must have absolute and instantaneous control
210 over their owned genomic data; 2) Lifecycle Data Encryption - data must remain encrypted throughout
211 its lifecycle in the system; 3) Verifiability - includes data integrity verifiability and computation process
212 verifiability. Our realization Govername includes three layers that work synergistically, including (1) a
213 consensus layer to manage user agreements; (2) a computing layer for secure computation, and (3)
214 an application layer for genomic applications.
215
216 The consensus layer is a blockchain that establishes the ownership of genomic data (see
217 'Techniques used at the Consensus Layer' subsection in Methods). The blockchain stores 1)
218 user permissions settings, 2) metadata and hashes for each query, 3) the source code of
219 supported genomic analysis tasks. Specifically, one's ownership of her genomic data should
220 be universally recognized, and her modifications to the permissions of her genomic data
221 should not have different versions across different nodes in the blockchain. For each query,
222 (i) the encrypted result, (ii) the individuals involved in serving the query, and (iii) metadata
223 are stored on the blockchain. Owners can achieve auditability by either (a) checking
224 requests that she replied with the access token, or (b) reconstructing the entire logs from the
225 access requests. Moreover, with the support of metadata, hashes and source code, the
226 workflows in Govername are transparent and reproducible by anyone, thus resolving
227 disputes.
228
229 The computing layer is for aggregating the storage and computation resources of multiple
230 parties with algorithms (see 'Techniques used at the Computing Layer' subsection in
231 Methods). The design of the computing layer focuses on 1) how genomic data is accessed,
232 2) how the genomic analysis tasks are performed, 3) how multiple parties cooperate to
233 participate in a task. The input of the computing layer is some encrypted data, while the
234 output is fixed-form results of some genomic analysis tasks. Apart from the final output, all
235 intermediate information is computable but cannot be decrypted. The computing layer is
236 responsible for outputting reliable results for tasks, with the computing process being
237 verifiable.
238
239 The application layer works as an interface for users who want to use the functions in
240 Govername (see 'Design focuses at the Application Layer' subsection in Methods).
241 Considering the steep learning curve of cryptography and secure computation, a user-
242 friendly interface is needed in Govername, while all modules related to privacy and security
243 should be encapsulated within the consensus layer and computing layer. The design of the
244 application layer, on the other hand, focuses on determining who can use Govername and
245 how different users can utilize Govername, where users can simply ask questions
246 predefined by the interface and receive responses. Moreover, as is requested by VER, when
247 users question the reliability of computational results, they should be allowed to request
248 evidence from the interface provided by the application layer and designate someone to
249 verify the data integrity or computation integrity.
250

251 The Workflow of Govername

252



253
254 Figure 2. The workflow of Govername. A query entity can ask the application layer a fixed-form question.
255 The application layer will then ask the consensus layer for qualifying data owners. The blockchain
256 managed at the consensus layer will send requests to qualifying data owners, and receive access
257 tokens (See 'How to encrypt genomic data' subsection in Methods) from consenting data owners for
258 the downstream homomorphic encryption-based computation. Next, the computing layers will pull the
259 relevant encrypted data blocks of the consenting data owners from storage nodes and perform
260 homomorphic encryption-based computation with the access tokens provided by the consensus layer.
261 No data is decrypted during the computation, except for that the final computation result will be
262 decrypted by the computing layer, and be returned to the query entity with a fixed-form answer.
263
264 The workflow of Govername is shown in Figure 2, and the necessary participants in the
265 workflow can be found in the 'Necessary supporting parties in Govername' subsection in
266 Methods. To use Govername, a query entity can submit fixed-form queries to the application
267 layer. For example, one can ask, "What's the genotype distribution of rs6053810 for
268 congenital heart disease patients?". After checking data owners' on-chain consent, the
269 consensus layer will send a request to the data owners for an access token (details shown in
270 the 'How to encrypt genomic data' subsection in Methods), which can make part of their
271 genomic data accessible to computing layer. After the access tokens for all data owners
272 involved have been collected, the computing layer will pull data from the storage nodes,
273 perform secure computation and return an answer to the query entity through the interface of
274 application layer (details shown in the 'How computing layer works' subsection in Methods).
275 Noteworthy, both access tokens and genomic data are utilized in encrypted form. Apart from
276 the fixed-form computation results, no other information is decrypted, thus fulfilling the
277 principle of LDE.
278

279 In general, a data owner is required to be actively responding to requests (specifically,
280 sending access token) from the blockchain, otherwise her data cannot be accessed and
281 would be excluded from analysis. However, it is impractical to require all the data owners to
282 be online and responsive around the clock. Therefore, in Govername, an option is given to

283 data owners to register a precomputed access token so that Governome will skip the data
284 owner and proceed with the token for computing. With this option, a data owner does not
285 need to be active for her data to be used. The registered access token does not need to be
286 recomputed until the next refresh of the computing layer. Details about the precomputed
287 access token can be found in the 'Precomputed access token' subsection in Methods.
288

289 Supported genomic analysis tasks in Governome

290 The application layer has defined a list of genomic analysis tasks, including individual variant
291 query, cohort study, GWAS analysis, and forensics. This section shows the functionalities of
292 the genomic analysis tasks and who can use the functionalities.
293

294 Individual variant query allows data owners to explore their own genomic information.
295 Interesting examples including, if someone is interested in whether she suffers alcohol flush
296 reaction after consumption, she can check-up variant rs671²¹ that causes aldehyde
297 dehydrogenase 2 deficiency. If a male individual wants to know if he needs to prepare for
298 early-onset hair loss, he can check-up variant rs6152²² that increases risk of baldness. In
299 Governome, one can input an rsID²³ and get the result of her own genotype.
300

301 Cohort study allows users to examine the genotype distribution of interested rsIDs relevant
302 to one or more demographics or phenotypes. GWAS analysis allows users to compare a
303 disease cohort against a normal cohort at the interested rsIDs, with p-values returned as
304 results. Cohort study in Governome should obey k-anonymity constraints²⁴. That is, a cohort
305 requires a minimum of k individuals to avoid the risk of being re-identified. The k in
306 Governome is configurable, and Governome returns an error if an analysis forms a cohort
307 with below k individuals. Detailed descriptions of the algorithms used for GWAS are in the
308 'HE-based GWAS analysis' subsection in Supplementary Methods.
309

310 Forensics analysis fulfills public security and legal purposes, such as anti-human-trafficking.
311 Given a set of genotypes, Governome can return a list of matching individuals registered in
312 the system. Such an application can bring high social value and is considered to be one of
313 the most important applications of a huge-scale owner-governed genomics database, in
314 addition to research and discovery. However, it is also dangerous, and it compromises
315 personal identity if being misused. Therefore, forensics analysis is exclusive to governmental
316 authorities, and in Governome, we allow a data owner to exclude herself from all forensics
317 analysis, observing our promise to give data owners ultimate control of their data. Forensics
318 analysis can be conducted among all participating individuals in the system, or a smaller
319 group shortlisted by hospitals according to some known demographic characteristics and
320 phenotypes.
321

322 Based on the supported genomics analysis tasks available in Governome, we generally
323 distinguished three types of users that demand different analysis permissions (Table 1). The
324 three types are data owners, authorities, and research entities. The ability to perform an
325 individual variant query is exclusively granted to data owners. Using blockchain, data
326 ownership is immediately confirmed, and an individual variant query is processed instantly.
327 In contrast, forensics analysis is exclusive to authorities due to its risk of reidentification. All
328 types of users are allowed to conduct cohort studies in Governome. For a cohort study, if

329 there is a sample list meeting the k-anonymity constraint, the query is processed without
330 further authentication or qualification reviews. The types of users are expandable, and the
331 allowed tasks are configurable in Govername.

332

333 Table 1. Genomics analysis tasks allowed for different user groups.

| | Ind. variant query | Cohort study | Forensics |
|-------------------|--------------------|--------------|-----------|
| Data owners | ✓ | ✓ | ✗ |
| Authorities | ✗ | ✓ | ✓ |
| Research entities | ✗ | ✓ | ✗ |

334

335 Noteworthy, although Govername has only implemented a few common genomics analysis
336 tasks, it has no limit of having more tasks as long as they can be implemented at the
337 application layer. However, any new tasks need to be sufficiently analyzed and discussed
338 before introducing them into Govername to avoid unintended privacy risks.

339

340 Computational performance of Govername

341 We evaluated Govername's computational performance of 1) Generating proofs for an
342 access token, and 2) Homomorphic encryption based computation. These are the two most
343 computationally demanding procedures in Govername. Govername is implemented with
344 programming language Go version 1.21, and all benchmarks were done using the same
345 programming language and version.

346 Generating proof for access token

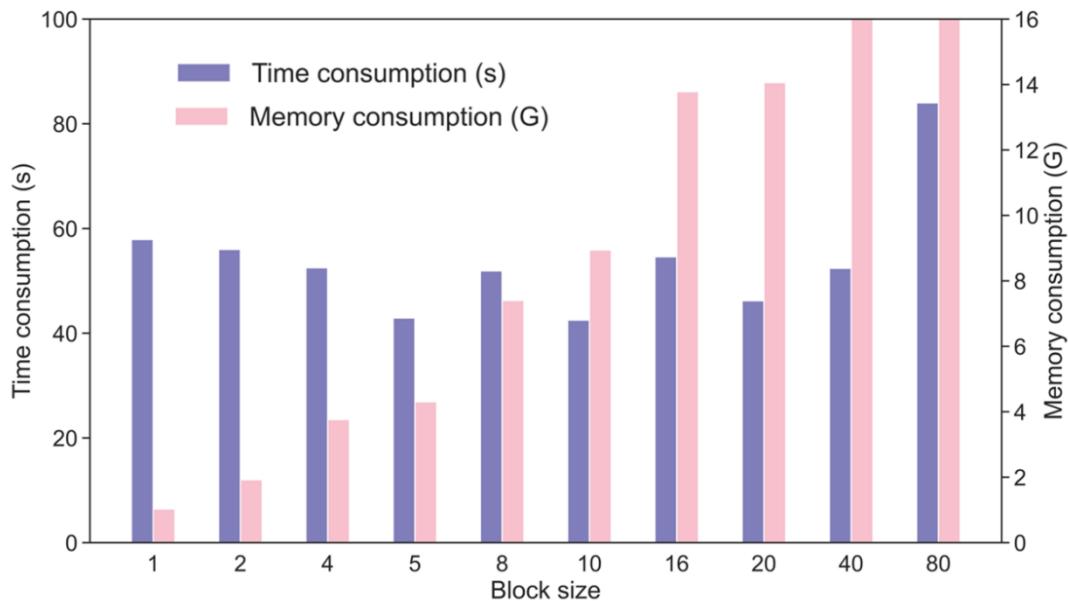
347 As mentioned in the workflow of Govername, a data owner should respond to the blockchain
348 and return an access token if consenting the data access request. An access token is the
349 encryption form of an 80-bit key²⁵ kept by a data owner. Apart from the access token, she
350 needs to provide some evidence to show that her 80-bit key is not tampered. Here we have
351 chosen ZK-SNARK (zero-knowledge Succinct Non-interactive Argument of Knowledge)²⁶ as
352 the solution to provide evidence. ZK-SNARK enables a data owner to prove that, without
353 revealing any part of the 80-bit key, 1) she holds the valid 80-bit key according to a hash
354 saved on-chain, and 2) she submitted an access token generated from the valid 80-bit key.
355 More details about why we have chosen ZK-SNARK is given in the 'Techniques used at the
356 Computing Layer' subsection in Methods.

357

358 The time and memory consumptions are shown in Figure 3. We used a laptop with an Apple
359 M1 CPU and 16GB of RAM, mimicking an average setting of a data owner. The time
360 consumption shows how long it takes to generate a proof and it implies the minimum time a
361 data owner can respond to a data request. The memory consumption shows the peak
362 memory used to generate a proof and it implies how much memory is needed in a data
363 owner's device in order to respond to a data request. The 80 bits in a key can be used
364 together to generate a proof, or be divided into smaller blocks to generate multiple proofs
365 before merging into a single proof (details given in the 'Zero-knowledge proof for access
366 token generation' subsection in Supplementary Methods). The memory consumption
367 increases linear to the block size, but time consumption may vary.

368

369



370

371 Figure 3. Performance of using ZK-SNARK to generate a proof for an 80-bit key using configurable
372 block sizes ranging from 1 to 80. The memory consumption of block size 40 and 80 exceeded the
373 available memory in our testing device (16GB), and was using memory swap. The exact numbers
374 shown in the figure are given in Supplementary Table 1.

375

376 Our benchmark showed that the memory consumption increased from 1.1GB at blocks size
377 1 to over 16GB at block size 40 or higher. The time consumption varied between block sizes,
378 and had an average of 57 seconds. Since a data owner's computational capacity is
379 commonly limited to a cell phone or a laptop, a low memory consumption is preferred. We
380 have chosen block size 1 as the default of Governome as it has minimal memory
381 consumption with a moderate time consumption. As a result, a data owner can generate all
382 the necessary information to respond to a data request with a memory consumption of
383 approximately 1GB and time consumption of about a minute, which are completely
384 acceptable.

385 Homomorphic encryption based computation

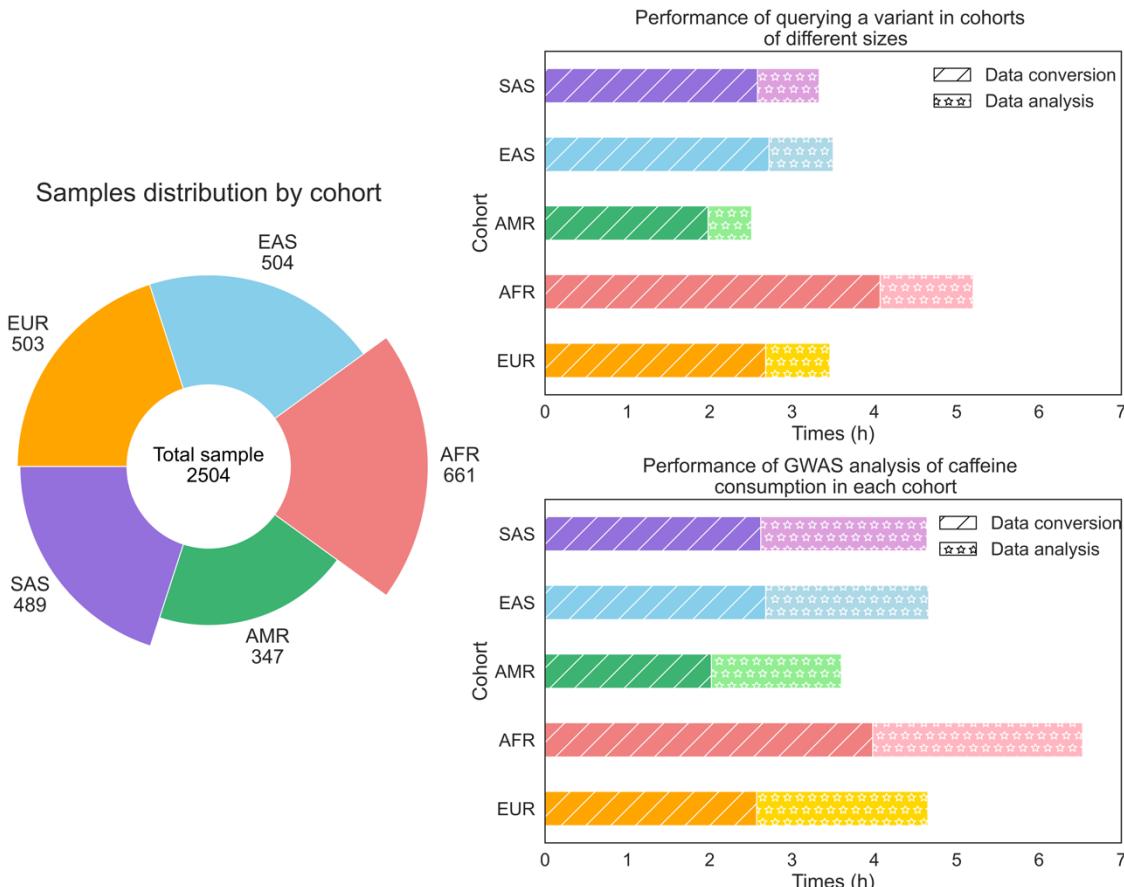
386 Homomorphic Encryption (HE)²⁷ is a cryptographic technique that enables computation on
387 encrypted data. In Governome, all data analyses are strictly HE-based computation
388 conducted at the computing layer. Computing nodes at the computing layer are usually
389 powerful servers with many CPU cores and much RAM. For the benchmarks in this section,
390 we used a server with two 32-core Intel Xeon Platinum 8369C 2.9GHz processors and
391 512GB of RAM. For any genomic analysis tasks, the two computational intensive steps are
392 benchmarked, including: 1) data conversion from stream ciphertext (smaller in size for HE-
393 based computing (details given in the 'Computation setup in Governome' subsection in
394 Methods), and 2) data analysis that uses HE-based computation. For samples, we used the
395 1000 Genomes Project (1kGP) dataset²⁰ comprising the whole genome variants of 2,504
396 individuals. The mock-up phenotypes of the 2,504 individuals were provided by the Hail
397 library and are available from its tutorial²⁸. The extracted phenotypes were already
398 normalized as either binary or categorical variables. We divided the samples into five cohorts
399

400 for our benchmarks according to the five superpopulations: Africans (AFR), Admixed
401 Americans (AMR), East Asians (EAS), Europeans (EUR), and South Asians (SAS) defined
402 in 1kGP.

403 Individual variant query and cohort study

404 Individual variant query is the simplest task in Govername. Our benchmark showed that
405 using a single CPU core, querying any random variant in an individual used at most 15
406 minutes to return a result. Cohort study, in comparison, demands much more computations,
407 especially when the cohort size is large, and when GWAS analysis is needed. In cohort
408 study, Govername allows inputting rsIDs to specify the variant of interests, and demographic
409 characteristics and phenotypes for choosing samples. If a cohort study query generates no
410 error, Govername will return the number of chosen samples, and the genotypes ratio of the
411 chosen samples at each rsID. The performance of querying a variant in five cohorts and all
412 2,504 1kGP samples is shown in Figure 4. Generally, the time consumption of both data
413 conversion and data analysis increased linearly against the number of samples in a cohort.
414 Querying a variant in all 2,504 samples was finished in about 18 hours (13h16m for data
415 conversion and 4h37m for data analysis). More CPU cores can be used for parallel
416 computing when querying more than a variant. The results show that Govername can
417 support any population scale because the linear increase in computation matches the
418 expected linear increase in computing nodes when more individuals are introduced to the
419 system.

420



421
422 Figure 4. Performance of cohort study, including 1) querying a variant, and 2) GWAS analysis of
423 CaffeineConsumption. The exact numbers shown in the figure are given in Supplementary Table 2
424 and 3.

425

426 For GWAS analysis, a p-value is calculated between the case samples and control samples
427 at each rsID. We have chosen the phenotype 'CaffeineConsumption' to divide the samples
428 in each cohort into case (CaffeineConsumption > 4) and control (CaffeineConsumption ≤ 4)
429 samples. The performance of GWAS analysis on rs6053810 is shown in Figure 4. The
430 results have shown that, while the number of samples of each cohort remains the same,
431 data conversion took a similar amount of time, while data analysis took longer due to the
432 algorithmically more complicated p-value computation. Govername allows multiple data
433 analysis tasks to be combined, so data conversion needs to be done just once.

434 Forensics

435 Forensic genetics relies heavily on analyzing short tandem repeat (STR) loci²⁹. In our
436 benchmark, we have chosen 13 STR loci³⁰ commonly used in forensics for analysis. One
437 can carry out forensics analysis in Govername using cohort analysis at the interested STR
438 loci with all samples in the system included in the cohort. However, the analysis will take
439 excessively long if not impossible to finish when millions of samples are stored in the
440 system. Therefore, we have added an auxiliary data block that stores only the genotype of
441 the 13 STR loci for each individual (see the 'Auxiliary data block' subsection in
442 Supplementary Methods). The auxiliary data block is small and specific for forensics
443 analysis. Thus, data conversion can be massively sped up when only forensics analysis is
444 needed. Noteworthy, auxiliary data block can include any number of variants for a specific
445 analysis task in Govername not limited to forensics.

446

447 When conducting a forensics analysis, an authority needs to input a list of STR loci with the
448 genotype it is searching for. Additionally, demographic characteristics and phenotypes can
449 be used to reduce the number of samples to be inspected. For each sample, Govername will
450 output a Boolean vector showing a match or mismatch of genotype at each STR loci. As
451 explained in the 'Necessary supporting parties in Govername' subsection in Methods,
452 sample IDs in Govername are de-identified. Thus, outside Govername, in order to know the
453 real identity of a matching individual, an authority needs to undergo legal procedures to get a
454 warrant and further work with hospitals.

455

456 We tested the performance of the above design on 2,504 1kGP samples. Data conversion
457 took 5 minutes and 51 seconds, while data analysis took 4 minutes. The performance is
458 acceptable if the number of candidates for forensics analysis can be effectively narrowed
459 down by known demographic characteristics and phenotypes.

460

461 Comparing Govername to previous solutions

462 In this section, we compared Govername against existing genomic data management
463 systems on the three properties of owner-governance. For OA, we extended it into two
464 evaluable dimensions including Permission Control and Auditability. Similarly, LDE was
465 extended into Storage Encryption and Computation Encryption, VER was extended into
466 Data Integrity Verifiability and Computation Process Verifiability. For each system being
467 compared, we assigned either "fulfilled", "partially fulfilled" or "not fulfilled" for each of the six
468 dimensions, the results are shown in Figure 5.

469

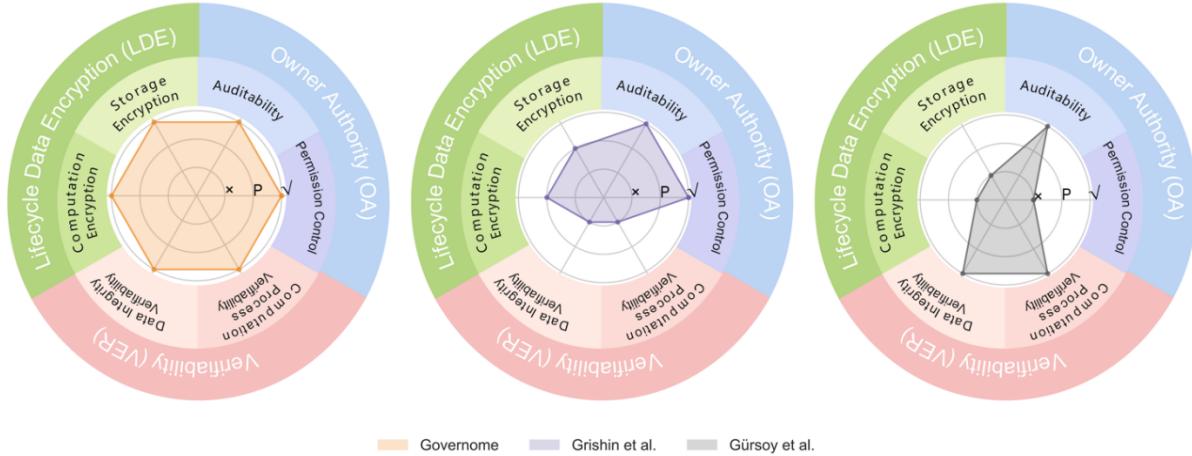
470 Existing human genomic databases are primarily government-funded centralized databases,
471 such as dbGaP⁵, UK Biobank⁶, and AllofUS⁷, which typically directly avail the data to
472 successful applicants. Some other databases are distributed, but they are still centrally
473 managed and are more like an aggregation of government-funded centralized databases,
474 such as GA4GH beacon⁹. These databases are centralized and have no capacity of owner-
475 governance, but these are among the most important human genome databases that have
476 promoted the development of genomics in the past decade.

477
478 Unlike the traditional human genome databases, Govername is decentralized and owner-
479 governed. There have been similar endeavors that have pushed the field forward, but they
480 are short in one or more dimensions that owner-governance requires.

481
482 Grishin et al.¹⁸ used a permissioned blockchain that restricts the set of entities that have
483 write-access to the chain, and hence they have achieved full Permission Control and
484 Auditability. They used HE in both computation and storage. But while HE ciphertext is many
485 times larger than the original text in size, they have chosen to only store the HE ciphertext of
486 those who shared their data. This still allows an instantaneously revocation of data access,
487 but resharing data requires uploading the HE ciphertext from the data owner again, which is
488 disincentive to data sharing and an active control of the data permission. The requirement
489 that data owners always need to hold an unencrypted full copy of their data is also what we
490 have avoided in Govername. Thus, we consider Grishin et al. has only partially fulfilled
491 Storage Encryption. In terms of Computation Encryption, we also consider Grishin et al. as
492 partially fulfilled because they used a HE scheme that supports only addition operation,
493 which limited the type and scale of genomic analysis tasks they can support. Grishin et al.
494 has no mechanism to ensure that 1) data owners would not fake their data while uploading,
495 and 2) computing parities would not fake the computing results.

496
497 Gürsoy et al.¹⁷ used a private blockchain to store BAM (sequencing raw data and
498 alignments) and VCF data without encryption. They achieved Auditability with the use of a
499 blockchain, but since anyone can see everyone's data on the chain, it puts any sort of
500 Permission Control in vain. They obviously also lack Computation Encryption and Storage
501 Encryption. However, they fulfilled both Data Integrity Verifiability and Computation Process
502 Verifiability because the genomic data is permanently stored on-chain, and any computation
503 can be repeated and verified by others because data is not encrypted.

504



505
506 Figure 5. Comparing Governorome against existing genomic data management systems on six
507 dimensions including Permission Control, Auditability, Storage Encryption, Computation Encryption,
508 Data Integrity Verifiability, and Computation Process Verifiability. Each dimension was assigned
509 evaluation of either "fulfilled" (✓), "partially fulfilled" (P), or "not fulfilled" (✗).
510

511 Discussion

512 In this paper, we reviewed the limitations of existing genomic data management systems.
513 We defined the three properties that lead to the full-fulfillment of owner-governance, which is
514 the next step of cryptogenomics. We developed Governorome, the first realization of a secure,
515 transparent, decentralized data management system that enables owner-governed genomic
516 data management. With Governorome, we demonstrated that the three properties required by
517 owner-governance, including 1) Owner Authority, 2) Lifecycle Data Encryption, and 3)
518 Verifiability, can be fulfilled simultaneously. Governorome can do a series of genome data
519 analysis tasks that support the routines of different user groups, including 1) data owners, 2)
520 authorities, and 3) research entities. We benchmarked the performance of Governorome and
521 showed its potential to manage large population-scale genomic data.
522

523 At the computing layer, Governorome uses Torus ³¹, a third-generation homomorphic
524 encryption technique, for homomorphic encryption based computation. To our best
525 knowledge, Governorome is the first to use third-generation homomorphic encryption
526 technique for decentralized genomic data management and computing. The second-
527 generation homomorphic encryption techniques used in previous solutions, such as
528 TrustGWAS ¹², suffer from significant performance degradation when the computing
529 becomes more complicated. This is because the efficiency of second-generation
530 homomorphic encryption relies heavily on single-instruction multiple-data optimization ³²,
531 which becomes difficult if not impossible when computation becomes complicated and
532 contains excessive branches. Third-generation homomorphic encryption technique has no
533 such limitation, and has enabled Governorome to support more complicated genomic data
534 analysis tasks and future expansion.
535

536 There are several aspects that could be improved in Governorome as future works. First, the
537 current implementation supports only rsID as the variant index. rsID is reference genome

538 agnostic and is verified to be effective and sufficient for personal genome at the stage by
539 public personal genome sequencing services, including 23andMe and Ancestry. However,
540 rsID is incapable of representing every single variant locus of a genome. While more and
541 more personal genomes are now whole-genome sequenced, Govername should support the
542 storage of VCF (Variant Call Format). In fact, Govername can be configured to use VCF to
543 store variants easily. However, the effectiveness of storing the whole genome in personal
544 genomics remains to be debated by the community, especially as we provision that
545 resequencing a genome will get cheaper than storing them permanently.

546
547 Govername stores only genomic data and relies on hospitals or institutions that are eligible
548 to host demographic and phenotypic data to shortlist qualifying samples for analysis. It is a
549 practical design considering how most electronic health records are collected and organized.
550 However, technically, Govername can also store and manage demographic and phenotypic
551 data.

552
553 Genomic data in Govername is intended to be permanently stored. However, considering
554 the significant advancements in quantum computing, Govername's security in post-quantum
555 era will become a new challenge. Currently, Govername is not quantum-resistant. In the next
556 step, we will explore optimizing cryptographic methods and privacy protocols to achieve
557 post-quantum reliability.

558

559 Methods

560 Feasible approaches to fulfill the three properties of owner- 561 governance

562 In this section, we discuss the techniques used in Govername and how they serve to fulfill
563 the three properties of owner-governance. As shown in Figure 1, Govername comprises
564 three layers: a consensus layer for authority management, a computing layer for secure
565 computation, and an application layer to make use of the other two layers for genomic
566 applications. At the consensus layer, Blockchain is used to enable dynamic permission
567 control, and Zero-knowledge Proof is used to enforce data integrity. At the computing layer,
568 cryptographic techniques, including Homomorphic Encryption, stream cipher, and Secure
569 Multi-party Computation, are used to fulfill secure computation. At the application layer,
570 several design focuses are introduced to establish the fundamental guidelines for building an
571 efficient owner-governed genomic data management system.

572

573 Techniques used at the Consensus Layer

574 **Why use Blockchain?** Owner Authority strictly requires decentralization, as centralization
575 would technically inevitably jeopardize owners' control of their data despite how many non-
576 technical promises have been made. Blockchain, as a proven decentralized solution that can
577 achieve consensus, is considered a natural choice for an owner-governed genomic data
578 management system. Blockchain can be configured to ensure that no party can exercise
579 power on others' data except for their own. Due to the transparent and traceable nature of

580 blockchain, data owner can access their consent and data usage logs at any time, thus
581 ensure auditability. Blockchain can also be used to enforce consensus on computation
582 results so fraud by minorities can be avoided. Both public blockchain and private blockchain
583 are applicable to Govername. While renowned public blockchains are trusted for their
584 decentralization and diversification of users, hence more suitable for publicly or
585 internationally initiated genome hosting, a private blockchain is more flexible and cost-
586 effective for locally initiated genome hosting, in which decentralization is less of a concern.
587

588 **Why use Zero-knowledge Proof?** Lifecycle Data Encryption requires genomic data to
589 remain encrypted throughout its lifecycle in the system. Ciphertext at both storage and
590 computation makes it hard if not impossible to avoid tampering or fraud through traditional
591 means, such as revealing the data or computation results for public scrutiny. In order to
592 ensure the genomic data and computation results are not tampered with or frauded, we use
593 zero-knowledge proof. Zero-knowledge proof²⁶ allows a prover to generate a proof for a
594 proposition without revealing any of its input. In Govername, any data loaded and stored is
595 encrypted with stream cipher, meanwhile a stream cipher key (SCK) is generated and held
596 by the data owner. When a data owner needs to prove she is providing untampered data,
597 Govername uses Zero-knowledge proof to prove that she is providing an encryption of the
598 right SCK to make genomic data accessible without revealing any part of the SCK.
599 Tempered SCK will lead to a different hash that mismatches what has been saved on-chain,
600 thus failing the proof.

601 Techniques used at the Computing Layer

602 **Why use Homomorphic Encryption?** The only way to ensure no data leakage is either no
603 data to leak or leakage doesn't matter. In Govername, LDE mandates that no plaintext exists
604 in the system. Thus, a solution that supports verifiable computation with ciphertext only is
605 needed. Homomorphic Encryption (HE)²⁷ is such a solution that produces deterministic
606 computation results verifiable by all users in the system, using only encrypted data and
607 requiring zero decryption. In contrast, hardware-based solutions, like Intel SGX (Software
608 Guard Extensions) and AMD Memory Encryption Technology, cannot fulfill LDE because
609 they require data to be decrypted when exiting the hardware that supports the same
610 solution. They also cannot fulfill VER because their computational results cannot be easily
611 verified by users who lack the same hardware solution. The details about the HE schemes
612 used in Govername can be found in the 'Homomorphic Encryption Scheme' subsection in
613 Supplementary Methods.
614

615 **Why use a stream cipher?** We use HE to fulfill LDE in Govername. However, conversion
616 from plaintext to HE ciphertext (ciphertext capable of HE-based computations) expands the
617 data size by over three orders of magnitude³¹, making it inefficient if not impossible to store
618 HE ciphertext. In Govername we solve the problem by encrypting plaintext with a cipher that
619 1) does not significantly increase the size of ciphertext so the ciphertext can be stored
620 efficiently, and 2) can convert from ciphertext to HE ciphertext on-the-fly and without
621 decryption for analysis. Stream cipher³³ fulfills these requirements. In Govername, with the
622 use of stream cipher, stream cipher ciphertexts are stored, and will be converted to
623 temporary HE ciphertexts when analysis needs them. More details about how genomic data
624 is encrypted and saved, along with how the stream ciphertext is transferred into HE

625 ciphertext are available in the 'Storage and computation setup in Govername' subsection in
626 Methods.

627

628 **Why require multiple parties for the generation of HE key?** Genomic data that are
629 converted into HE ciphertext can be used for analysis, and as the nature of HE, the
630 computation results are also in HE ciphertext. Inevitably, the results are required to be
631 decrypted to become readable before leaving the system. The decryption requires the key
632 that was used to encrypt HE ciphertext. However, that implies that anyone who holds the
633 complete key can decrypt the HE ciphertext to obtain the original genomic data or
634 computation results. In Govername, we 1) required a collaborative generation of a complete
635 key, and 2) avoided any single parties having a copy of the complete key. Our solution uses
636 Threshold Fully Homomorphic Encryption ³⁴ (ThFHE), which is a type of Secure Multi-party
637 Computation ³⁵ (SMPC). SMPC enables multiple parties to collaborate to generate a key
638 without disclosing the input of any parties, and it ensures the honesty of all parties.
639 Furthermore, SMPC can be used not only for key generation but also for HE ciphertext
640 decryption. So, without revealing the complete key to any party, SMPC then uses the key
641 and the multiple parties who generated the key to decrypt the computation results. The
642 correctness of computation results is ensured by the SMPC protocol ³⁶⁻³⁸. If not using SMPC,
643 one might think of isolation measurements such as limiting the interactions between
644 computing parties (that do compute but are not eligible to see the results) and a HE key
645 holder (that are eligible to see the results), so the computing parties cannot see any
646 intermediate results without the key. However, compliance with such measurements is not
647 algorithmically guaranteed, which is against VER in Govername.

648 Design focuses at the Application Layer

649 The consensus layer and computing layer together enable owners to have around-the-clock
650 full governance and security of their data. Application layer, on the other hand, is about how
651 to make use of genomic data. An application layer should 1) provide necessary but minimal
652 functions to accomplish different genomic analysis tasks, 2) interface well with the
653 consensus and computing layers, and 3) operate efficiently even with encrypted data. The
654 design of the application layer of Govername has the following major focuses.
655

656 **The application layer defines what the users can do.** The application layer defines what
657 could be done with the genomic data stored in the system by providing a set of functions.
658 This set of functions should be meticulously designed to remain necessary but minimal so as
659 to fulfill data management and analysis tasks. The functions are immutable once introduced
660 into the layer so everyone can verify and trust these functions. Availing a function to only a
661 specific set of users enables users to have different roles in the system.
662

663 **The application layer shall do nothing more than the consensus layer and computing**
664 **layer allow.** The application layer uses only the interface the consensus layer and
665 computing layer offered. This allows the applications to have better flexibility, while critical
666 functions such as permission control and result verification are enforced by the consensus
667 and computing layers. For example, data access permission changes received at the
668 application layer will be handled by the consensus layer immediately without a possible
669 delay at the application layer.
670

671 **The application layer needs to work efficiently.** Data analysis in Governome works solely
672 with HE ciphertext. A function that works with HE ciphertext needs to be compiled into the
673 combination of single operations like addition over small integer field, the performance of
674 which is expected to be significantly different from, if not much slower than, what the function
675 is supposed to be working with plaintext. Thus, the efficiency of the functions that deal with
676 massive amounts of data at the application layer needs to be carefully examined.
677

678 Necessary supporting parties in Governome

679 In Governome, besides data owners, multiple parties with different roles are involved to form
680 a robust genomic data analysis system. Their duties and importance are explained as
681 follows.

- 682 1. Hospitals or institutions that are eligible to host demographic and phenotypic data: In
683 Governome's design, it hosts only genotypic data and does not host phenotypic data.
684 This is an effective measurement to 1) isolate different types of critical data, and 2)
685 avoid a single party getting over-powerful. The participating hospitals and institutions
686 connect to the blockchain. Their communications are encrypted and algorithmically
687 verifiable. If a query is asking for a specific cohort with demographic or phenotypic
688 constraints, Governome will ask each participating hospital or institution to provide a
689 list of qualified and anonymous sample IDs. Hospitals and institutions are allowed to
690 return an incomplete (or even empty) list of qualifying samples because they also
691 have the power that equals the Governome to refuse individual data usage. The
692 sample IDs are anonymous by using data owners' blockchain address.
- 693 2. Super users that will never withdraw from the system: Both the consensus layer and
694 computing layer of Governome require multiple active users to maintain functioning.
695 While data owners are granted full governance of their data in Governome, few of
696 them might be active users that can host the blockchain and support the computing
697 in Governome. Super users are a group of users that run servers and can provide
698 storage (i.e., storage nodes) and computing resources (i.e., computing nodes) to
699 keep a Governome system running. Within the data usage lifecycle of genomic data
700 in Governome, super users are responsible for checking hashes and proofs to
701 ensure correctness, pulling data from the storage nodes, converting data into HE
702 ciphertext, and performing the actual computations. The computation results are
703 ultimately decrypted collaboratively by the super users and returned to the query
704 entities through the interface of the application layer. Super users are usually
705 academic institutions, governmental authorities, hospitals, and pharmaceutical
706 companies - the major stakeholders in the system who will mostly benefit from a
707 stable and growing Governome system. In Governome, we require two or more
708 super users to be involved in security-critical procedures, including SMPC, HE key
709 generation, and computation results decryption. While super users have a higher
710 responsibility to keep a Governome system operational, they have data usage
711 privileges identical to all data owners.
- 712 3. Temporary computing nodes that temporarily provide additional computing power.
713 Large-scale cohort studies and GWAS analyses are usually conducted by
714 institutional users who are willing to contribute temporary computing nodes in return
715 for some speed up in obtaining a result.

716

717 Storage and computation setup in Governome

718 How to encrypt genomic data

719 In Governome, raw genomic data is encrypted with stream ciphers and stored in distributed
720 storage nodes that are organized by a blockchain. As data owners have around-the-clock full
721 governance of their data, they are supposed to hold the SCK and are being asked for it
722 every time their data is being used for computing. However, a practical concern is that data
723 owners might leak their SCK due to incidents such as device loss or data theft. The risk is
724 accumulative and gets more significant when the sample size increases. To address the
725 issue, Governome uses hospitals as an additional SCK holder. Instead of holding a complete
726 SCK, data owner and hospital each holds only a part of the key. Governome collects the two
727 partial access tokens (HE ciphertext form of the two partial keys) from the data owner and
728 hospital, and recovers full access token (HE ciphertext form of the complete SCK) with
729 secure computation supported by HE (see Supplementary Figure 1). Details about how
730 genomic data is segmented and stored are described in the 'Data Segmentation' subsection
731 in Supplementary Methods, and the discussion of security concerns can be found in the
732 'Security of the data blocks' subsection in Supplementary Methods. This design reduces the
733 risk of leaking the complete SCK. Noteworthy, although hospital also holds part of data
734 owner's SCK, it has no right over data owner's genomic data because in Governome, data
735 ownership is ascertained through consensus on the blockchain rather than through the
736 possession of SCK.

737 Precomputed access token

738 When a data owner's data is asked to be included for analysis, she is requested to submit an
739 access token generated from her SCK and a Governome-given HE key not only for her data
740 to be used for HE-based computing, but also as a gesture of granting access. However, this
741 behavior requires data owners to respond actively; otherwise, their data would not be
742 included for analysis. This requirement might be too demanding for some data owners who
743 are always willing to be involved in analyses as long as their privacy is protected.
744 Precomputed access token is such a mechanism in Governome to allow a sharing data
745 owner to register a precomputed access token for accessing all her data blocks (see 'Data
746 Segmentation' subsection in Supplementary Methods) so that she does not need to respond
747 to Governome for their data to be used.

748 How computing layer works

749 The computing layer in Governome involves multiple parties for managing and using stream
750 ciphertext and HE ciphertext, as shown in Supplementary Figure 2. The stream ciphertext
751 from storage nodes will be converted to computable HE ciphertext, using the two partial
752 access tokens collected from the data owner and hospital. The computing layer can carry
753 out different genomic analysis tasks according to the query. The generation of HE key uses
754 SMPC, and therefore no single computing node has the complete copy of it, eliminating the
755 chance that a single computing party could peek or tamper with the HE key. The analysis
756 results are in encrypted form and will be decrypted using SMPC before returning to a query
757 entity.

758
759

760 Code availability

761 Governome is available open-source at <https://github.com/HKU-BAL/Governome> under the
762 BSD 3-Clause license.
763

764 Data availability

765 The authors declare that all data supporting the findings, including source data and analysis
766 results of this study are available at <http://www.bio8.cs.hku.hk/governome/>.
767

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772

773 Author contributions

774 R. L. conceived the study. J. Z. and R. L. designed algorithms, implemented Governome. J.
775 Z. and J. S. designed the experiments. R. L., J. Z., J. S., Y. R., M. H. A. and K. C. analyzed
776 the data and drafted the paper. Y. Z., L. C., and Y. Z. evaluated the benchmarking results.
777 All authors reviewed the manuscript.
778

779 Competing interests

780 The authors declare no competing interests.
781

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