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Age-Related Changes in Hair Shaft Protein Profiling and Genetically Variant Peptides

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Keywords

Proteomic profiling, genetically variant peptides, human hair, ageing, forensic investigation

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Competing Interests

DPS, RSY and MGD are/were employees of Procter & Gamble. The authors declare no conflict of interest, with the exception of GJP, who has a patent based on use of genetically variant

peptides for human identification (US 8,877,455 B2, Australian Patent 2011229918, Canadian Patent CA 2794248, and European Patent EP11759843.3, GJP inventor). The patent is owned by Parker Proteomics LLC. Protein-Based Identification Technologies LLC (PBIT) has an exclusive license to develop the intellectual property and is co-owned by Utah Valley University and GJP. This ownership of PBIT and associated intellectual property does not alter policies on sharing data and materials. These financial conflicts of interest are administered by the Research Integrity and Compliance Office, Office of Research at the University of California, Davis to ensure compliance with University of California Policy.

1 **Abstract**

2 Recent reports highlight possible improvements in individual identification using proteomic
3 information from human hair evidence. These reports have stimulated investigation of
4 parameters that affect the utility of proteomic information. In addition to variables already
5 studied relating to processing technique and anatomic origin of hair shafts, an important variable
6 is hair ageing. Present work focuses on the effect of age on protein profiling and analysis of
7 genetically variant peptides (GVPs). Hair protein profiles may be affected by developmental and
8 physiological changes with age of the donor, exposure to different environmental conditions and
9 intrinsic processes, including during storage. First, to explore whether general trends were
10 evident in the population at different ages, hair samples were analyzed from groups of different
11 subjects in their 20's, 40's and 60's. No significant differences were seen as a function of age,
12 but consistent differences were evident between European American and African American hair
13 profiles. Second, samples collected from single individuals at different ages were analyzed.
14 Mostly, these showed few protein expression level differences over periods of 10 years or less,
15 but samples from subjects at 44 and 65 year intervals were distinctly different in profile. The
16 results indicate that use of protein profiling for personal identification, if practical, would be
17 limited to decadal time intervals. Moreover, batch effects were clearly evident in samples
18 processed by different staff. To investigate the contribution of storage (at room temperature) in
19 affecting the outcomes, the same proteomic digests were analyzed for GVPs. In samples stored
20 over 10 years, GVPs were reduced in number in parallel with the yield of identified proteins and
21 unique peptides. However, a very different picture emerged with respect to personal
22 identification. Numbers of GVPs sufficed to distinguish individuals despite the age differences
23 of the samples. As a practical matter, three hair samples per person provided nearly the maximal
24 number obtained from 5 or 6 samples. The random match probability (where the log increased in
25 proportion to the number of GVPs) reached as high as 1 in 10^8 . The data indicate that GVP
26 results are dependent on the single nucleotide polymorphism profile of the donor genome, where
27 environmental/processing factors affect only the yield, and thus are consistent despite the ages of
28 the donors and samples and batchwise effects in processing. This conclusion is critical for
29 application to casework where the samples may be in storage for long periods and used to match
30 samples recently collected.

31

32 **Introduction**

33 Protein profiling (comparison of relative protein expression levels) and proteomic genotyping
34 (inferring single nucleotide polymorphisms in the genome using the proteome) for human hair
35 comparison and individual identification have shown promise as potential tools for forensic
36 investigation. For example, large inter-individual differences in protein profile are evident in hair
37 shafts (Laatsch et al, 2014). Studies using human twins (Wu et al, 2017) support the conclusion
38 reached using inbred mouse strains (Rice et al, 2012) that differences in profile have primarily a
39 genetic basis. Corneocyte proteins of the hair shaft (Wu et al, 2017), epidermis (Borja et al,
40 2019) and appendages provide an even more direct connection to genotype in their reflection of
41 individual allelic differences in the genome. Thus, detection of genetically variant peptides
42 (GVPs) containing single amino acid polymorphisms (SAPs) that could be matched to single
43 nucleotide polymorphisms (SNPs) in the coding region of the genome provides a more
44 discriminating way to infer the genotype and even ancestry of the donor (Parker et al, 2016).

45 From a forensic perspective, limitations on the use of samples for such identifications are
46 important to know. For example, recent findings show that the hair shaft is equally useful for
47 profiling or GVP analysis regardless of its state of pigmentation (Parker et al, 2019) or anatomic
48 site of origin (Chu et al, 2019; Milan et al, 2019), although GVP analysis can offer much greater
49 discrimination. A property that remains to be examined is the reproducibility of such samples
50 with age of donor or period of storage. This issue is pertinent because the protein content of
51 samples may change with the age of the donor at collection, and casework samples are often in
52 storage for many years. Thus, investigators are likely to compare samples from individuals at
53 different ages and originating many years apart.

54 First, to determine whether global changes in hair are evident with age, present work compares
55 protein profiles in samples from groups of individuals of different age. Samples collected at
56 roughly the same time are compared from American females in their 20's, 40's and 60's from
57 European and African backgrounds, also permitting investigation of the role of ethnic origin.

58 Second, to examine changes in hair from individuals over time, samples were compared in

59 protein profile and GVP content from 9 subjects at age intervals of 4 to 65 years. The results of
60 both studies are presented and reconciled.

61 **MATERIALS AND METHODS**

62 **Sample collection**

63 For analysis of samples from different age groups, hair was collected by a commercial supplier
64 from 30 African Americans (10 each of ages 20, 40, 60) and 40 European Americans (20 of age
65 20 and 10 each of ages 40 and 60), all female (Cohort 1). Samples are referred to as “African” or
66 “European” for simplicity. One sample from each donor was analyzed. To find the effect of age
67 on individuals, a second set of samples that had been collected at different times (stored at room
68 temperature) from nine individuals (A – E (Cohort 2) and F-I (Cohort 3), total three females and
69 six males), each analyzed in sets of 2-6 replicates (**Table S1**). According to donors, the hair was
70 not chemically treated (dyed, bleached, straightened). These samples were collected with
71 informed consent approved by the University of California Davis Institutional Review Board
72 (protocol 896494) and processed within a year.

73 **Sample processing for protein isolation and mass spectrometry**

74 In each case, aliquots of 4 mg were processed essentially as previously described (Laatsch et al,
75 2014) except for using 0.05 M ammonium bicarbonate instead of 0.1 M sodium phosphate buffer
76 during reduction and alkylation. Each cohort of samples was processed at a different time by a
77 different investigator. Hair protein digests from the age groups and from individuals were
78 randomized and analyzed by LC-MS/MS on a Thermo Scientific Q Exactive Plus Orbitrap mass
79 spectrometer essentially as previously described (Wu et al, 2017).

80 **Database searching and proteomic profiling based on weighted spectral counts and** 81 **statistical analysis**

82 Data files generated for the samples of age groups (Cohort 1) and the individuals A-E (Cohort 2)
83 were analyzed using X!Tandem (2016.10.15.2) to search a Uniprot human database with an
84 appended database of common human contaminants and an appended identical but reversed
85 (decoy) peptide database for estimating false discovery rates. The proteomics data are available

86 in the MassIVE repository as #MSV000085030, Proteome Exchange #PXD017771
87 (<https://massive.ucsd.edu/ProteoSAFe/dataset.jsp?task=4a43733eab0c45a0a78a7afc7ad4f685>).
88 Also, the data from Cohorts 2 and 3 have been deposited to the ProteomeXchange Consortium
89 via the PRIDE (Perez-Riverol et al, 2019) partner repository with the dataset identifier
90 PXD016169. Scaffold (version 4.8.2) was used to validate peptide and protein identifications.
91 Accepted protein identifications contained at least 2 identified peptides. False discovery rates
92 were estimated as 0.1% and 2.9% for peptides and proteins, respectively. The MS results were
93 analyzed as weighted spectral counts (with clusters containing shared peptides) after removal of
94 entries not genuinely present judging by their exclusive peptides. Differential protein abundance
95 analyses were conducted using the limma-voom Bioconductor pipeline, originally developed for
96 analysis of RNA-Seq data and applied here to weighted spectral counts (Ritchie et al,
97 2015). Standard errors of estimates were adjusted for correlation between replicates from the
98 same sample; subject was included as a fixed effect in all models. The R code is provided in
99 supplemental files.

100 **Protein profiling using PEAKS**

101 Label-free quantitation was performed on the LC-MS/MS datasets of individuals A-I (Cohorts 2
102 and 3) using PEAKS Studio 10.0 (Bioinformatics Solutions Inc., Waterloo, ON, Canada) to
103 obtain their protein profiles (Zhang et al, 2012). From 2 - 6 samples for each age from all nine
104 individuals amounting to a total of 67 datasets were analyzed against a validated UNIPROT
105 human reference proteome (uniprot-proteome_UP000005640_Human). Default settings of the
106 algorithm were employed except that the precursor mass error range and fragment ion were set to
107 10 ppm and 0.04 Da, respectively. Cysteine carbamidomethylation (+57 Da) was set as a fixed
108 post translational modification, while deamidation on glutamines and asparagines (+0.98 Da),
109 oxidation of histidines, tryptophan, and methionine (+15.99 Da), dioxidation of methionines
110 (+29.99 Da), pyroglutamation at glutamines (-17.02 Da) and glutamates (-18.01 Da), and
111 acetylation (+42.01) and formylation (+27.99) of N-termini and lysines were variable
112 modifications. The resulting datasets, filtered with a 1% false discovery rate, were analyzed
113 using the Q-module function of PEAKS Studio, and a heat map was generated by label free
114 quantitation for proteins with at least 2 fold difference in the levels among the groups and a
115 significance of 13 (p value = 0.05; $-10\log(0.05) = 13.01$). Due to batch effects identified by

116 comparing profiles of the most recent samples of Cohorts 2 and 3 (**Figure S1**) a collective
117 comparison of the profiles of individuals A-I was not performed.

118 **GVP analysis**

119 The data files of the nine individuals (A-I) sampled at different ages were searched to generate
120 GVP profiles to determine whether the individuals could be distinguished from each other by this
121 criterion. For GVP analysis, raw data files were submitted to X!Tandem peptide spectra
122 matching algorithm (Global Proteome Machine Fury, X!Tandem Alanine 149 (2016.10.15.2))
123 after conversion to MzML format by MSConvertGUI (Proteowizard 2.1
124 <http://proteowizard.sourceforge.net>). Default search parameters of the algorithm were used
125 except that the virus and prokaryote reference libraries were excluded and point mutations were
126 included in the search. Protein and peptide log(e) scores of -1, and fragment and parent mass
127 error of 20 ppm and 100 ppm, respectively, were used. The files generated by X!Tandem (.XML,
128 thegpm.org) were used to obtain the peptide data, which was then provided to/pasted into GVP
129 Finder (Goecker et al, 2019). From the list of putative GVPs, unique tryptic peptides carrying
130 log(e) scores of < -2 were used for GVP profiling if they displayed no other genetic or chemical
131 modifications (except N/Q deamidation, methionine oxidation, cysteine carboxymethylation and
132 N-terminal acetylation) and, if corresponding to a minor allele, with no major fragmentation
133 masses corresponding to the reference alleles. The GVPs observed in the current study were not
134 validated by DNA sequencing. However, the previously observed rate of false positive
135 identifications of 1.5-2% (Borja et al, 2019; Parker et al, 2016) using the employed method
136 provides high confidence in the GVP profiles. The mass spectrometry proteomics data from
137 Cohorts 2 and 3 have been deposited to the ProteomeXchange Consortium via the PRIDE
138 (Perez-Riverol et al, 2019) partner repository.

139 **Random match probability calculation**

140 Random match probabilities (RMPs) were calculated for the GVP profile of each sample using
141 the genotype frequencies of the identified loci from the 1000 Genomes Project Consortium
142 (2015). As all the studied subjects in Cohorts 2 and 3 were of European origin, only European
143 genotype frequencies were used for estimation of RMP. For the calculation, each SNP was
144 treated as independent except the multiple GVPs/alleles from one gene that were treated as one

145 locus. The frequency for the allele combination was then used to estimate the RMPs. The
146 product rule was applied to calculate the RMP for each specific GVP profile (Parker et al, 2016).

147 **Hierarchical clustering**

148 For statistical analysis, all the GVPs detected in the biological replicates were collated. GVPs
149 detected in one or more replicates were given the same weight. All the detections were assigned
150 the value “1”, and those that were not detected in the samples were assigned the value “0”. GVPs
151 that were either detected or not detected throughout the samples (and thus were without
152 probative value) were excluded from the analysis. Agglomerative hierarchical clustering with
153 complete linkage was performed based on the Euclidean distance data for the samples, and a
154 dendrogram for the clustering was plotted using the hclust function of R (Version 3.6.2) (Milan
155 et al, 2019).

156 **RESULTS**

157 **Hair proteome comparison among age groups**

158 To study the effect of age and ethnicity on the hair proteome, hair samples from European-
159 American and African Americans of three age groups (20s, 40s, 60s) were studied. The data
160 were analyzed against the Uniprot human database using X!Tandem (2016.10.15.2) and peptide
161 and protein identifications were validated using Scaffold (version 4.8.2). The weighted spectral
162 counts of 241 proteins were used for analyzing pairwise differences in protein profile. As
163 illustrated in **Table 1**, significant pair-wise differences were not detected in different age groups
164 within each ethnic category or within the ethnic groups of combined ages. However, some
165 significant differences between samples from African-American and European-American
166 subjects were discernable (**Figure 1**). Proteins higher in the African samples included TYRP1
167 (Tyrosinase Related Protein 1) and GPNMB (Glycoprotein Nonmetastatic Melanoma Protein B),
168 which participate in melanin biosynthesis (Kobayashi et al, 1998; Zhang et al, 2012), and are a
169 reflection of the higher melanin content in samples from the African-American cohort. In
170 addition, certain keratins (i.e., KRTs 1, 2, 5, 9, 10, 24) were among the proteins higher in level in
171 the African samples. Two proteins involved in membrane lipid metabolism, PLD3 (Gonzalez et
172 al, 2018) and LPCAT3 (Rong et al, 2015), were higher in the European hair samples. As the
173 cuticle cells are bounded by a protein membrane surrounded by lipids (Dias, 2015), the higher

174 number of cuticle layers in the European compared to African samples could contribute to the
175 differences in level of these hair proteins in the two populations. Other proteins higher in the
176 European samples are involved in autophagy (HSP90AA1, ATG9b), ribosomal function (RPS2,
177 EEF1D), and calcium binding (CALML5). The overall data obtained from Cohort 1 identified no
178 consistent proteomic differences in hair shafts as a function of age in the range of 20 to 60 years.
179 Likewise, the lack of overall proteomic differences precludes the possibility of global changes in
180 GVP profile as a function of age. Importantly, however, the data do not exclude the possibility
181 that age-related changes in protein abundance are not detected due to compensating individual
182 variation over time.

183 **Proteomic profile comparisons at different ages in given individuals based on weighted** 184 **spectral counts**

185 Because a lack of differences in the hair proteome as a function of age in unrelated individuals
186 could be attributed to compensating individual variation, a complementary analysis was also
187 conducted on recent hair samples and those that had been stored over 4 to 65 years from 9
188 individuals (Supplementary Table S1). Two different groups of subjects (Individuals A-E in
189 Cohort 2 and Individuals F to I in Cohort 3) were analyzed. For the first longitudinal study,
190 proteomic datasets from hair shafts from 5 individuals were processed, and significant
191 differences in pair-wise protein abundances among a total of 211 proteins were tabulated. As
192 shown in **Table 2**, data from three subjects (A, D, and E) showed few protein differences (0-6)
193 with age in two-way comparisons over periods of 4-11 years. Samples from one subject (C)
194 showed few differences (5-7) over a span of 6 years, but a substantial number (27) over 11 years.
195 One subject (B) showed a substantial number of differences (32) over a span of 65 years. As
196 shown in **Figure 2**, the protein profiles from a single subject at different ages were much closer
197 in distance than the profiles among different individuals. The data in **Table 2** indicated that
198 subjects D and E could be readily distinguished from all the other subjects, but some subject
199 combinations would be more difficult (e.g., A0 or A6 versus C6 or C11). Also the subjects B and
200 C had high levels of internal differences, but these were consistent with longer time frames, a 65
201 year storage time for subject B and an 11 year difference for subject C. Storage time of the hair
202 sample may have contributed to these differences in protein profiling, although physiological
203 changes due to subject aging cannot be excluded.

204 **Proteomic profile comparisons at different ages among individuals based on heatmaps**

205 An additional batch of hair samples (Cohort 3) was processed to expand the number of
206 longitudinal samples. The resulting proteomic profiles were bioinformatically processed to
207 obtain label free quantitation and subsequent heat maps using Q-module in the PEAKs™
208 software package (version 10.0) (Zhang et al, 2012). The samples were divided into two groups,
209 new (recent samples) and old (collected 7 or more years before present) based on the time since
210 collection. As can be seen in **Figure 3A**, when protein profiles were filtered based on a 2-fold
211 change and p-value of 0.05, little difference was seen in the proteomes of older and recent
212 samples when compared collectively. Only 3 protein differences were detected, one of which,
213 KRTAP7-1, was a structural protein and one, SEC23B, is involved in endosomal transport and
214 was significantly increased in pigmented hair (Parker et al, 2019). The low number of significant
215 differences, again, could be attributed to the higher variation in proteomic profiles from
216 individual to individual that could cancel statistically significant effects. Another analysis was
217 therefore conducted on the most extreme case, individual I, with a 44 year gap in subject age.
218 Samples from this individual showed 54 proteins that had a 2-fold change in abundance (p=0.05)
219 (**Figure 3B**) with fifty proteins higher in level in the recent samples compared to the older ones.
220 These included proteins reported to be concentrated in the cuticle (S100A3, KRT40, KRT82,
221 KRTAP16-1, 24-1, and 3-2) among other hair KRTs and KRTAPs (<http://www.proteinatlas.org>;
222 (Moll et al, 2008; Uhlén et al, 2015). The higher amounts of cuticle concentrated proteins in the
223 recent samples could reflect the loss of cuticle in the older samples (Thibaut et al, 2010). Four of
224 the proteins were higher in level in the older samples, SYNE2 (cytoskeletal protein), AKAP9
225 (scaffolding protein), and GFAP (an intermediate filament protein) (<http://www.proteinatlas.org>).
226 A similar analysis from individuals F, G, and H showed considerably fewer proteomic changes
227 over a period of 7 years with 2, 13, and 4 proteins respectively, differing among the stored and
228 recent samples.

229 **Genetically variant peptide analysis**

230 To determine the effect of potential sample degradation with storage, GVPs in each sample were
231 first identified and evaluated. The total number of unique peptides was also measured in each
232 proteomic dataset. Sample storage/age was not seen to affect the average number of identified

233 unique peptides in the samples over periods of <10 years (**Figure 4A**). However, decreases of
234 ~38, 27, and 33% of the unique peptides, relative to their corresponding recent samples (stored
235 <1 year), were observed in the samples B, C and I over storage periods of 65, 11 and 44 years,
236 respectively (**Figure 4A and Table S1**). These results are consistent with the previous
237 observations of a reduction in the complexity of proteomes over long periods of time, leading to
238 a loss/degradation of certain proteins (Thibaut et al, 2010; Parker et al, 2016). By contrast, the
239 samples from individual A did not show significant alterations in the amounts of detected
240 proteins or unique peptides over a period of 11 years. The samples from individual E at both ages
241 provided very low numbers of identified unique peptides (≈ 1200) and proteins (≈ 300) compared
242 to the average numbers observed in the other samples (≈ 3000 and ≈ 600 , respectively) (**Table**
243 **S1**), an example of a substantial individual effect.

244 Genetically variant peptide profiles were identified for each individual (A-I) in the longitudinal
245 study with 2 to 6 biological replicates. Overall, 237 different GVPs at 127 loci were identified
246 with 67 ± 18 GVPs per sample (**Table S2**). A straightforward relationship could not be made
247 between the age of the sample and the number of GVPs observed except for the individuals B, C,
248 and I (**Figure 4B**). The numbers of GVPs decreased 1.48 fold from 57.6 ± 8.5 to 36.6 ± 7
249 ($p=0.03$) in individual B, 1.5 fold from 63.3 ± 10.5 to 40.3 ± 14 ($p=0.015$) for individual C, and
250 2.1 fold from 63.6 ± 6 to 33 ± 3 ($p=0.007$), for individual I with storage over periods of 65, 11
251 and 44 years, respectively. However, the number of GVPs detected was seen to be proportional
252 to the number of identified unique peptides in the samples ($R=0.86$, **Figure 5A**) as also observed
253 by others (Catlin et al, 2019). GVP detections, when compared with the number of replicates
254 used for each sample, showed that three biological replicates provide enough information to
255 cover 97% of the GVPs, and adding more replicates is hardly more effective (**Figure S2**).

257 **Random match probability**

258 To calculate the random match probability (RMP) at each age, SNP profiles were inferred for
259 each of the samples from their respective GVP profiles. The genotype frequencies from the 1000
260 Genomes Project for the inferred SNPs were used to calculate the RMPs. The calculation
261 employed the product rule with complete independence between GVPs in different genes and
262 complete dependence with GVPs from the same gene. The calculated random match

263 probabilities ranged from 1 in 73 (for sample E1) to 1 in 185 million (for sample A3). The log of
264 the RMP was found to be proportional to the number of GVPs detected (**Figure 5B**) with rare
265 SNPs considerably increasing the RMPs.

266 **Hierarchical clustering**

267 Proteomic changes observed over 4-7 years were modest. However, more substantial changes
268 over time were observed proteomically in the older samples from 44 and 65 year intervals. This
269 was true for both total numbers of identified proteins (Table S1) and total unique peptide levels
270 (Figure 4A, Table S1). Significant changes were also observed due to batch effects between the
271 second and third cohort of longitudinal samples. A central question of this study was whether
272 these changes also affected the profile of GVP-based inferred SNP genotypes. Therefore, GVP
273 profiles of the individuals at different ages were also compared side by side. Samples from the
274 same individuals were found to carry a large proportion of GVPs common at all ages with some
275 unique GVPs (**Figure S3**). For the GVP profiles generated for individuals A-I, every GVP
276 detection was assigned a value 1 and a non-detection a value 0 to create a binary data file for
277 calculating Euclidean distances and from them to plot an agglomerative hierarchical clustering
278 dendrogram. As seen in **Figure 6**, samples collected at different time points from the same
279 individuals were clustered together, although distances among subjects varied. This includes the
280 samples that had the longest storage periods and greatest level of changes, individuals B and I. It
281 also includes samples from different cohorts of longitudinal samples, individuals A to E and F to
282 I, despite recognizable batch effects (Figure S1). This indicates that the GVP-inferred profiles of
283 SNP alleles were more dependent on individual genotypes than changes occurring as a result of
284 storage with proteome degradation and batch effects.

285 **DISCUSSION**

286 Previous work has shown that inbred mouse strains can be distinguished by their hair
287 protein profiles (Rice et al, 2012). Subsequently, human individuals were also shown to be
288 distinguishable in this way (Laatsch et al, 2014). Studies of monozygotic twins indicate that the
289 basis for such differences is largely genetic (Wu et al, 2017). That the twin profiles were not
290 found to diverge with age would be consistent with a lack of effect of age or changes with age in
291 the same direction within twin pairs. Present results support the latter alternative. Inasmuch as

292 the different hair shaft layers (e.g., cuticle) have different protein profiles from the rest of the
293 shaft (Laatsch et al, 2014), also reported for sheep wool (Koehn et al, 2010), changing
294 proportions of the layers over time as diameters change could result in altered profiles. Hair shaft
295 diameters reportedly change with age, decreasing in the elderly (Robbins et al, 2012; Kim et al,
296 2013). This finding is consistent with a report that the relative content of mRNAs encoding
297 keratins and keratin associated proteins in hair follicles also changes with age (Giesen et al,
298 2011). The basis for chronological ageing is multifactorial, but includes accumulation of
299 oxidative damage from ambient oxidants, ultraviolet radiation, copper content (Marsh et al,
300 2014) and air pollution (De Vecchi et al, 2019).

301 Present results indicate a lack of consistent population-wide changes, but some changes
302 are evident for individuals. This finding supports possible usefulness of hair shaft protein
303 profiling in distinguishing among individuals over short time periods, but it highlights a
304 dependence on a short interval between sample collections, a clear limitation. Finding a
305 substantially larger difference in subject C after 11 years compared to 5 or 6 years (27 versus 5
306 or 7) could be rationalized by a drift in profile. Comparing hair samples from individuals
307 collected at greater than 40 year intervals, as for subjects B and I, reveals a large drift. Such
308 changes could result from effects of normal ageing on hair follicle function/gene expression and
309 profile modifications due to exposure to different physicochemical factors during storage.
310 Therefore, proteomic profiling alone would not likely provide sufficient information to
311 distinguish individuals from each other on a large scale. Moreover, batch effects from processing
312 the samples at different times could confound use of a database of proteomic profiles for
313 individual identification.

314 GVP analysis, on the other hand, was found to be a powerful tool to identify the source of the
315 hair sample in each of the nine subjects studied despite the samples being stored even for periods
316 >40 years. GVP analysis permits calculation of random match probabilities, providing a
317 statistical basis for confidence in the results. The older samples of the individuals B and I,
318 although deficient in proteins and peptides detected, provided GVP profiles with RMPs of 1 in
319 nearly 1000 and 500, respectively. This capability is of particular interest for old and cold cases,
320 where hair is present as evidence and nuclear DNA is not available. The relation between the
321 number of unique peptides, GVPs, and the calculated RMPs testifies to the value of optimizing

322 sample processing procedures and ongoing efforts to maximize their yields in problematic
323 samples (e.g., from individual E).

324 The observation of lower unique peptide and protein yields with longer storage is
325 consistent with loss of cuticle in older hair samples (Thibaut et al, 2010; Solazzo et al, 2013).
326 This phenomenon could also rationalize the higher proportion in the recent samples of KRTAPs
327 found in the present study. A factor of potential importance is the chemical modification of
328 samples during long term storage. Deamidation, which has been linked with ageing of hairs
329 (Robinson and Robinson, 2004; Adav et al, 2018), was higher in samples stored over a period of
330 at least 10 years ($R=0.97$) (**Figure S4**). Other common chemical modifications were not
331 consistent in their direction of change. Nevertheless, this observation raises the prospect in
332 general of chemical modifications, some of which could depend on storage conditions. An
333 important area for future investigation is the impact on protein profiles, and especially on GVP
334 yield, of treatments individuals may use to reduce environmental damage, and common chemical
335 treatments that are known to induce considerable damage and to reduce protein yields (Marsh et
336 al, 2015).

337 **Conclusion**

338 The present study highlights that the hair, although very resilient in nature, could undergo
339 developmental and environmental changes over decades, resulting in drift in profile and thus
340 intra-individual variation. Therefore, proteomic profiling alone has limitations for human
341 identification. GVP profiles, in contrast, were seen to be more robust over periods as long as 65
342 years. The stored hair samples, despite losing a fraction of unique peptides and proteins, were
343 sufficient to provide high RMPs. These findings promise to be highly valuable in resolving
344 routine and even old cases where hair samples are available for investigation.

345 **REFERENCES**

346 1000 Genomes Project Consortium, Auton A, Brooks LD, Durbin RM, Garrison EP, Kang
347 HM, Korbel JO, Marchini JL, McCarthy S, McVean GA, Abecasis GR (2015) A global
348 reference for human genetic variation. *Nature* 526:68-74

349 Adav SS, Subbaiah RS, Kerk SK, Lee AY, Lai HY, Ng KW, Sze SK, Schmidtchen A (2018)
350 Studies on the proteome of human hair-Identification of histones and deamidated keratins.
351 *Scientific Reports* 8(1):1599

352 Borja T, Karim N, Goecker Z, Salemi M, Phinney BS, Naeem M, Rice RH, Parker GJ (2019)
353 Proteomic genotyping of fingerprint donors with genetically variant peptides. *Foren Sci Int:*
354 *Genet* 42:21-30

355 Catlin LA, Chou RM, Goecker ZC, Mullins LA, Silva DS, Spurbeck RR, Parker GJ, Bartling
356 CM (2019) Demonstration of a mitochondrial DNA-compatible workflow for genetically variant
357 peptide identification from human hair samples. *Foren Sci Int: Genet* 43:102148

358 Chu F, Mason KE, Anex DS, Jones AD, Hart BR (2019) Hair proteome variation at different
359 body locations on genetically variant peptide detection for protein-based human identification.
360 *Scientific Reports* 9(1):7641

361 De Vecchi R, da Silveira Carvalho Ripper J, Roy D, Breton L, Alexandre Germano Marciano
362 AG, de Souza PMB, de Paula Corrêa M (2019) Using wearable devices for assessing the impacts
363 of hair exposome in Brazil *Scientific Reports* 9(1):13357

364 Dias MF (2015) Hair cosmetics: an overview. *Int J Trichology* 7:2-15

365 Goecker ZC, Wills BM, Salemi SR, Phinney BS, Rice RH, Walsh S, Parker GJ (2019)
366 Biogeographic classification of European and African hair using genetically variant peptides.
367 30th Annual International Symposium on Human Identification Poster #64

368 Gonzalez AC, Schweizer M, Jagdmann S, Bernreuther C, Reinheckel T, Saftig P, Damme M
369 (2018) Unconventional trafficking of mammalian phospholipase D3 to lysosomes. *Cell Reports*
370 22:1040-1053

371 Kim SN, Lee SY, Choi MH, Joo KM, Kim SH, Koh JS, Park WS (2013) Characteristic
372 features of ageing in Korean women's hair and scalp. *Br J Dermatol* 168:1215-1223

373 Kobayashi T, Imokawa G, Bennett DC, Hearing VJ (1998) Tyrosinase stabilization by Tyrp1
374 (the brown locus protein). *J Biol Chem* 273:31801-31805

375 Koehn H, Clerens S, Deb-Choudhury S, Morton J, Dyer JM, Plowman JE (2010) The
376 proteome of the wool cuticle. *J Proteome Res* 9:2920-2928

377 Laatsch CN, Durbin-Johnson BP, Rocke DM, Mukwana S, Newland AB, Flagler MJ, Davis
378 MG, Eigenheer RA, Phinney BS, Rice RH (2014) Human hair shaft proteomic profiling:
379 individual differences, site specificity and cuticle analysis. *PeerJ* 2:e506

380 Marsh JM, Iveson R, Flagler MJ, Davis MG, Newland AB, Greis KD, Sun Y, Chaudhary T,
381 Aistrup ER (2014) Role of copper in Photochemical damage to hair. *Int J Cosmetic Sci* 36:32-38

382 Marsh JM, Davis MG, Flagler MJ, Sun Y, Chaudhary T, M Mamak M, McComb DW,
383 Williams REA, Greis KD, Rubio L, Coderch L (2015) Advanced hair damage model from ultra-
384 violet radiation in the presence of copper *Int J Cosmetic Sci* 37:532-541

385 Milan J, Wu P-W, Salemi M, Durbin-Johnson B, Rocke DM, Phinney BS, Rice RH, Parker
386 GJ (2019) Comparison of protein expression levels and proteomically-inferred genotypes using
387 human hair from different body sites. *Foren Sci Int: Genet* 41:19-23

388 Moll R, Divo M, Langbein L (2008) The human keratins: biology and pathology. *Histochem*
389 *Cell Biol* 129:705-733

390 Parker G, Goecker Z, Franklin R, Durbin-Johnson B, Milan J, Karim N, De Leon C, Matzoll
391 A, Borja T, Rice B (2019) Proteomic genotyping: using mass spectrometry to infer SNP
392 genotypes in a forensic context. *For Sci Intl: Genet Suppl Ser* 7:664-666

393 Parker GJ, Leppert T, Anex DS, Hilmer JK, Matsunami N, Baird L, Stevens J, Parsawar K,
394 Durbin-Johnson BP, Rocke DM, Nelson C, Fairbanks DJ, Wilson AS, Rice RH, Woodward SR,
395 Bothner B, Hart H, Leppert M (2016) Demonstration of protein-based human identification using
396 the hair shaft proteome. *PLoS One* 11(9):e0160653

397 Perez-Riverol Y, Csordas A, Bai J, Bernal-Llinares M, Hewapathirana S, Kundu D, Inuganti
398 A, Griss J, Mayer G, Eisenacher M, Pérez E, Uszkoreit J, Pfeuffer J, Sachsenberg T, Yilmaz S,
399 Tiwary S, Cox J, Audain E, Walzer M, Jarnuczak AF, Ternent T, Brazma A, Vizcaíno JA (2019)

400 The PRIDE database and related tools and resources in 2019: improving support for
401 quantification data. *Nucl Acids Res* 47(D1):D442-D450

402 Rice RH, Bradshaw KM, Durbin-Johnson BP, Rocke DM, Eigenheer RA, Phinney BS,
403 Sundberg JP (2012) Differentiating inbred mouse strains from each other and those with single
404 gene mutations using hair proteomics. *PLoS One* 7:e51956

405 Ritchie ME, Phipson B, Wu D, Hu Y, Law CW, Shi W, Smyth GK (2015) limma powers
406 differential expression analyses for RNA-sequencing and microarray studies. *Nucl Acids Res*
407 43(7):e47

408 Robbins C, Mirmirani P, Messenger AG, Birch MP, Youngquist RS, Tamura M, Filloon T,
409 Luo F, Dawson TLJ (2012) What women want - quantifying the perception of hair amount: an
410 analysis of hair diameter and density changes with age in caucasian women. *Br J Dermatol*
411 167:324-332

412 Robinson NE, Robinson AB (2004) Amide molecular clocks in drosophila proteins: potential
413 regulators of aging and other processes. *Mech Ageing Dev* 125:259-267

414 Rong X, Wang B, Dunham MM, Hedde PN, Wong JS, Gratton E, Young SG, Ford DA,
415 Tontonoz P (2015) Lpcat3-dependent production of arachidonoyl phospholipids is a key
416 determinant of triglyceride secretion. *Elife* 4:e06557

417 Solazzo C, Dyer JM, Clerens S, Plowman J, Peacock EE, Collins MJ (2013) Proteomic
418 evaluation of the biodegradation of wool fabrics in experimental burials. *Int Biodeterior*
419 *Biodegrad* 80:48-59

420 Thibaut S, De Becker E, Bernard BA, Huart M, Fiat F, Baghdadli N, Luengo GS, Leroy F,
421 Angevin P, Kermaol AM, Muller S (2010) Chronological ageing of human hair keratin fibres. *Int*
422 *J Cosmetic Sci* 32:422-434

423 Uhlén M, Fagerberg L, Hallström BM, Lindskog C, Oksvold P, Mardinoglu A, Sivertsson Å,
424 Kampf C, Sjöstedt E, Asplund A, Olsson I, Edlund K, Lundberg E, Navani S, Al-Khalili
425 Szigartyo C, Odeberg J, Djureinovic D, Takanen JO, Hober S, Alm T, Edqvist P-H, Berling H,
426 Tegel H, Mulder J, Rockberg J, Nilsson P, Schwenk JM, Hamsten M, von Feilitzen K, Forsberg
427 M, Persson L, Johansson F, Zwahlen M, von Heijne G, Nielsen J, Pontén F (2015) Tissue-based
428 map of the human proteome. *Science* 347:394 (1260419)

429 Wu P-W, Mason KE, Durbin-Johnson BP, Salemi M, Phinney BS, Rocke DM, Parker GJ,
430 Rice RH (2017) Proteomic analysis of hair shafts from monozygotic twins: Expression profiles
431 and genetically variant peptides. *Proteomics* 17:13-14, 1600462

432 Zhang J, Xin L, Shan B, Chen W, Xie M, Yuen D, Zhang W, Zhang Z, Lajoie GA, Ma B
433 (2012) PEAKS DB: de novo sequencing assisted database search for sensitive and accurate
434 peptide identification. *Mol Cell Proteomics* 11(4):M111.010587

435 Zhang P, Liu W, Zhu C, Yuan X, Li D, Gu W, Ma H, Xie X, Gao T (2012) Silencing of
436 GPNMB by siRNA inhibits the formation of melanosomes in melanocytes in a MITF-
437 independent fashion. *PLoS One* 7(8):e42955

438 **Table 1**

439 Pairwise comparisons of differentially expressed proteins by age and ethnic origin.*

441

442	A	<u>A20's</u>	<u>A40's</u>		B	<u>E20's</u>	<u>E40's</u>	
443		A40's	0			E40's	0	
444		A60's	0	0		E60's	0	0
445								
446	C	<u>20's</u>	<u>40's</u>		D	<u>A20's</u>	<u>A40's</u>	<u>A60's</u>
447		40's	0			E20's	8	
448		60's	0	0		E40's		6
449						E60's		2
450	E	<u>All A</u>						
451		All E	19					

453 *Ethnic groups are indicated by African (A) and European (E) and age groups by 20's, 40's and
 454 60's. The numbers in table indicate the number of proteins with significant differences in
 455 expression level.

456 **Table 2**

457 Pairwise comparison of proteins significantly different in expression level (weighted spectral
 458 counts) in two-way comparisons.*
 459

	A6	A11	B0	B65	C0	C6	C11	D0	D5	E0	E4
A0	2	0	34	4	64	7	7	23	22	206	132
A6		6	13	17	30	2	6	7	11	227	131
A11			30	15	56	6	11	26	23	168	103
B0				32	26	17	35	14	16	147	120
B65					88	23	9	24	26	196	132
C0						5	27	54	42	99	105
C6							7	10	9	35	28
C11								38	28	168	93
D0									1	135	118
D5										204	127
E0											3

460
 461 *Subjects are identified by letter and years since the first collection (0). Comparisons within the
 462 same individual from different years are in bold italic. The numbers in the table indicate the
 463 number of differentially expressed proteins.

464

465 **Figure Legends**

466 **Figure 1.** Proteins differing in hair samples from African and European subjects. Shown are the
 467 ratios of relative amounts of proteins that differed significantly, judging by weighted spectral
 468 counts, between the samples collected from African and European subjects.

469 **Figure 2.** Distances in protein expression levels between samples from single individuals and
 470 between subjects. Box plots of Euclidean distances between samples, based on weighted spectral
 471 counts. The solid line on each box indicates the median, the lower and upper box edges indicate
 472 the 25th and 75th percentiles, respectively, and the lower and upper whiskers indicate the
 473 smallest and largest observations lying within 1.5 interquartile ranges of the box edges,
 474 respectively.

475 **Figure 3.** Heatmap showing differences in the proteomic composition of the newly and
 476 previously collected samples of (A) cohort 3 (individuals F-I), and (B) individual I at two times
 477 points with a difference of 44 years. The numbers after the hyphens in the sample names
 478 represent the storage time of the samples.

479 **Figure 4: Unique peptides (A) and GVPs (B) in samples from individuals at different ages.**
 480 The lines of different color show values (averages and standard deviations) for individuals at the

481 ages indicated. Significantly lower values in the unique peptides were observed in the stored
482 samples of individuals B, C and I marked by asterisks. Periods of storage are indicated by the
483 time span between points for given subjects.

484 **Figure 5.** The number of GVPs vs (A) the unique peptides identified in each sample and (B)
485 calculated random match probabilities. The graph shows that the higher the number of unique
486 peptides identified in a sample, the higher will be the number of GVPs observed (p value =
487 0.0001) and the higher the random match probabilities calculated (p value = 0.003).

488 **Figure 6.** Hierarchical clustering dendrogram of all the samples from individual subjects. Based
489 on the Euclidean distances among the samples, the clustering shows that GVP profiles can
490 distinguish individuals despite differences in hair collection and storage times.

Ratio (European-American/African-American)

3

2

1

0

Figure 1

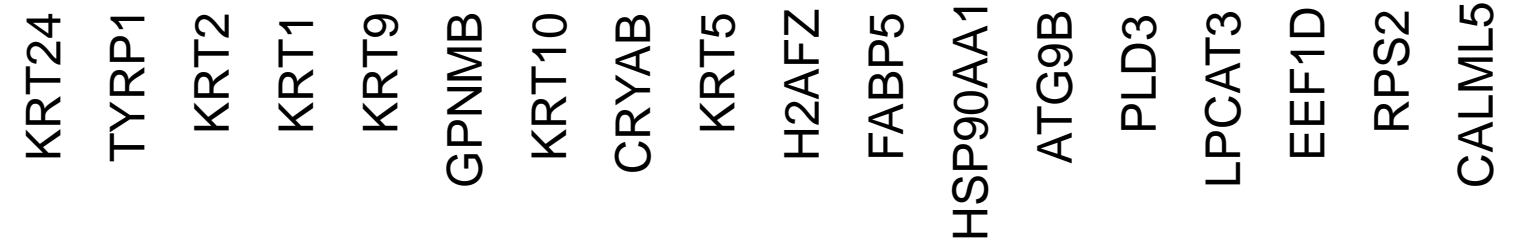
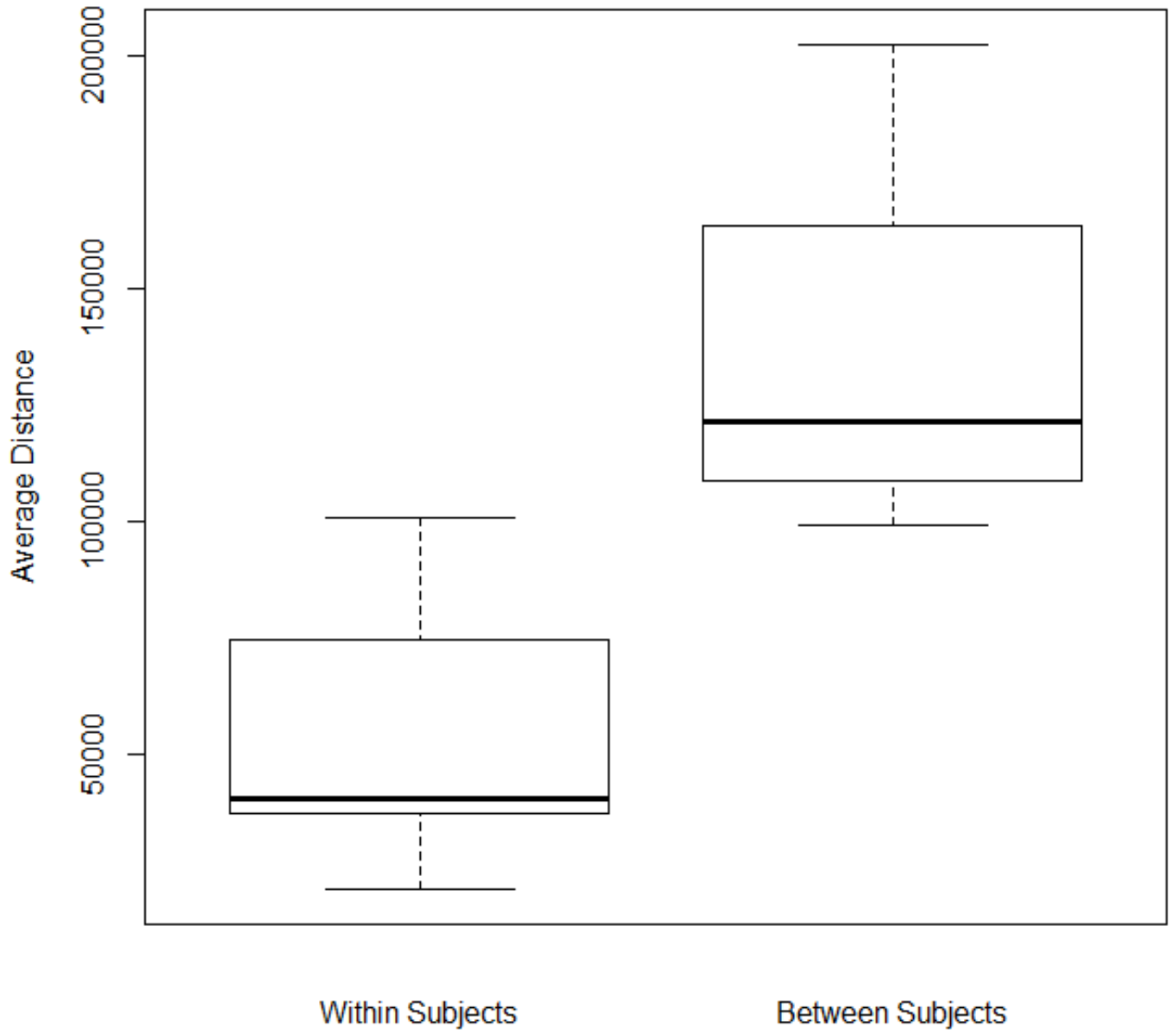


Figure 2



A

● A ● B ● C ● D ● E ● F ● G ● H ● I

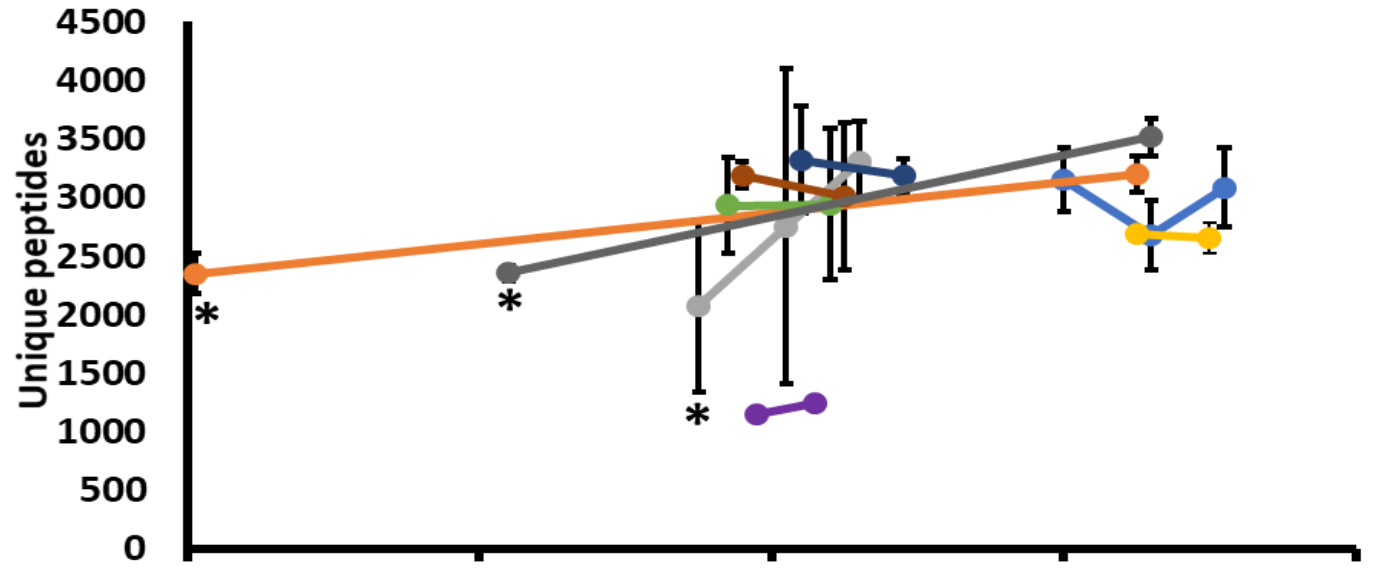


Figure 4

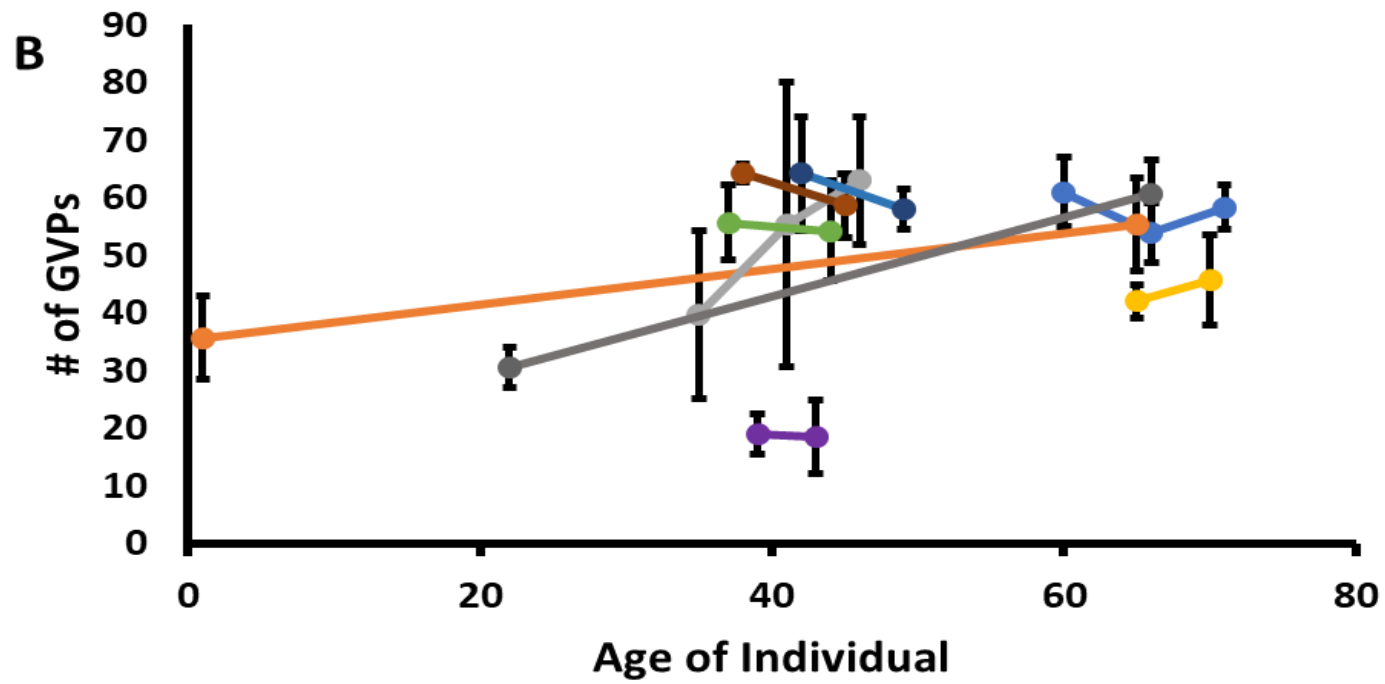
B

Figure 5

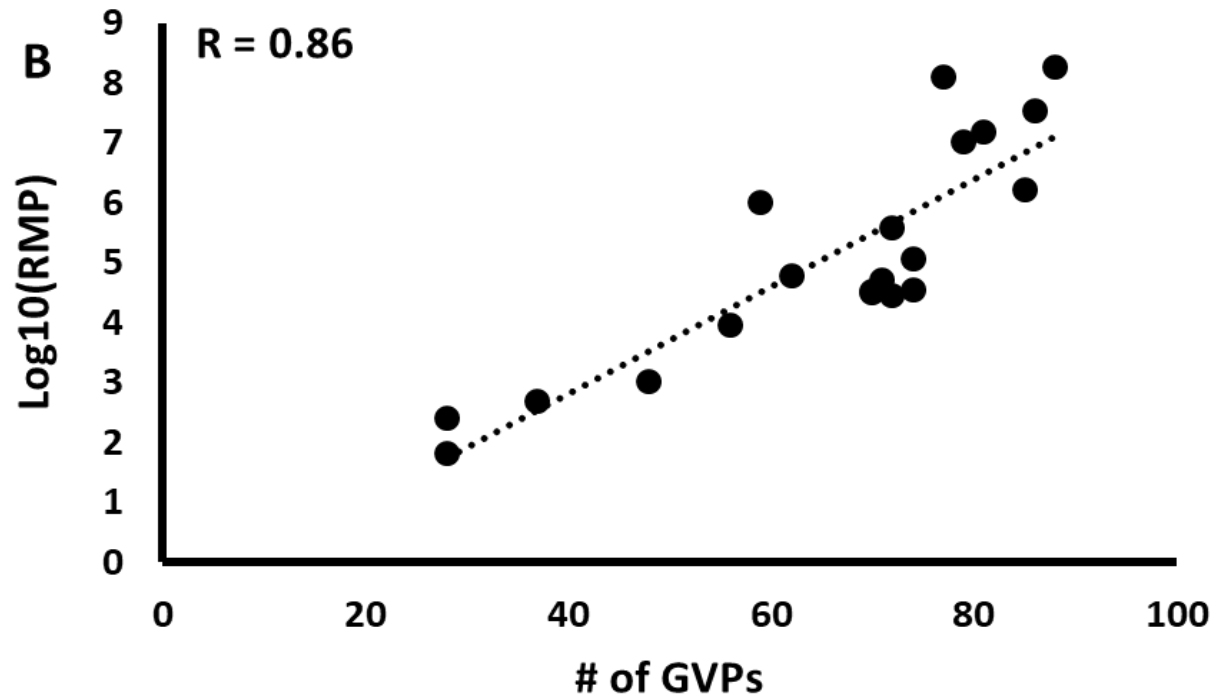
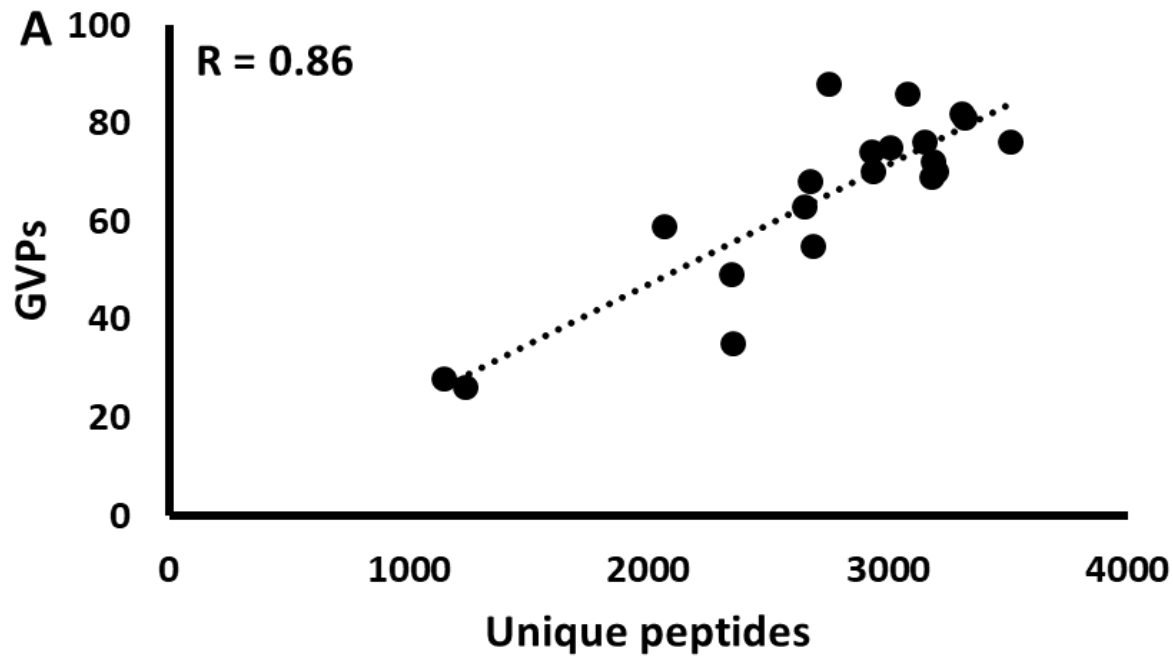


Figure 6

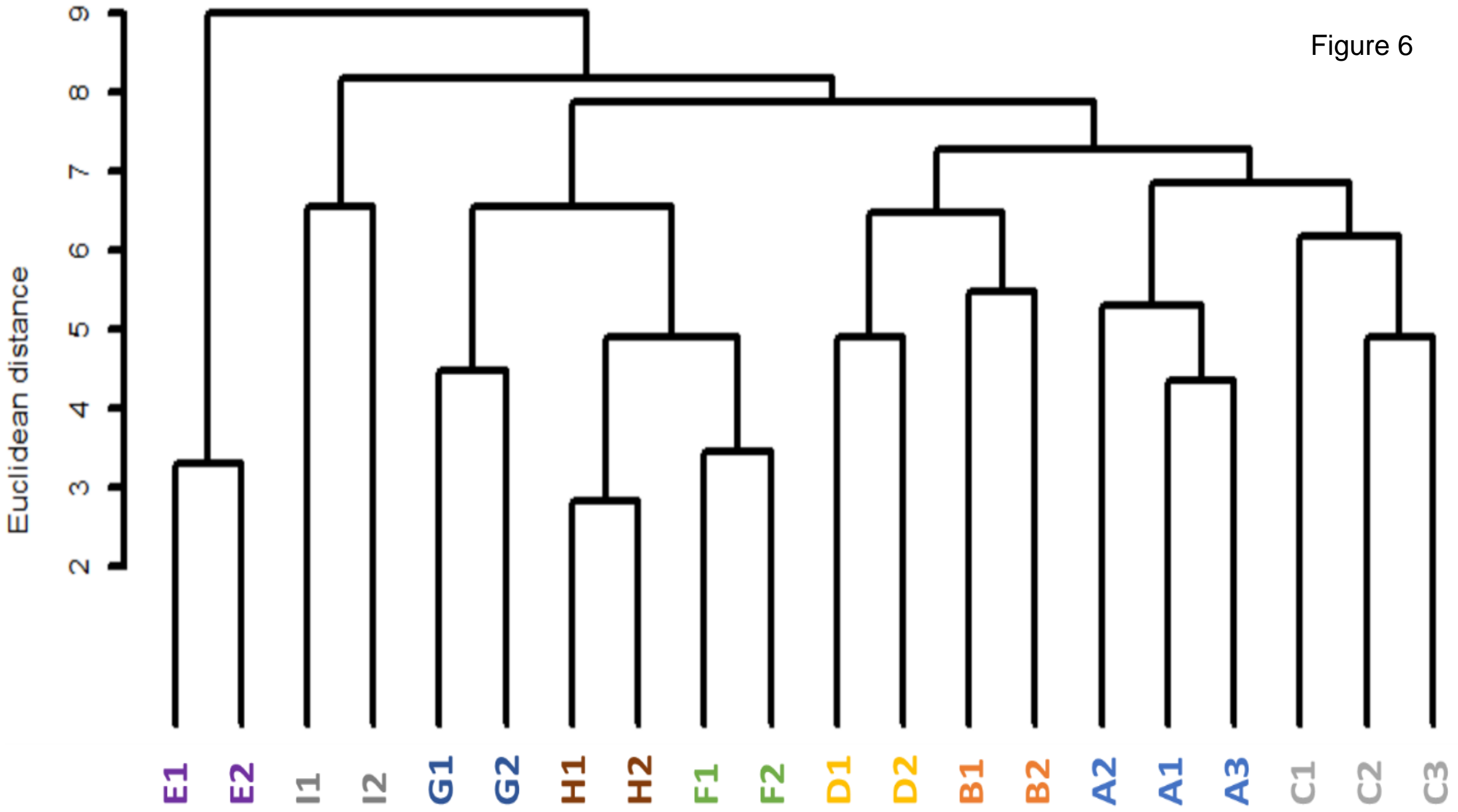


Table S1. Details of samples used in the study.

Sample Name	Collection Year	Age of Individual	Age of Sample	Sex (M/F)	Cohort	Identified Proteins	Unique Identified Peptides	Average Identified Protein \pm SD	Average Unique Peptides \pm SD
A1 A1 A1	2005	60	11	M	2	671 651 634	3337 3288 2842	652 \pm 18	3156 \pm 273
A2 A2 A2	2011	66	5	M	2	591 573 548	2757 2919 2354	571 \pm 22	2677 \pm 291
A3 A3 A3	2016	71	1	M	2	674 603 740	3241 2697 3309	672 \pm 69	3082 \pm 335
C1 C1 C1	2005	35	11	M	2	567 324 523	2547 1221 2439	471 \pm 130	2069 \pm 736
C2 C2 C2	2011	41	5	M	2	296 643 756	1223 3273 3760	565 \pm 240	2752 \pm 1346
C3 C3 C3	2016	46	1	M	2	672 644 702	3553 2911 3453	678 \pm 29	3305 \pm 345
B1 B1 B1	1951	< 1	65	M	2	575 575 563	2545 2216 2281	571 \pm 7	2347 \pm 174
B2 B2 B2	2016	65	1	M	2	687 639 693	3038 3212 3352	673 \pm 30	3200 \pm 157
D1 D1	2011	65	5	F	2	603 641	2662 2714	622 \pm 27	2688 \pm 36
D2	2016	70	1	F	2	623	2585	609 \pm 42	2651 \pm 128

D2						642	2799		
D2						562	2570		
E1	2012	39	4	M	2	274	1157	282 ± 18	1148 ± 15
E1						269	1130		
E1						302	1156		
E2	2016	43	1	M	2	275	1226	304 ± 41	1236 ± 14
E2						333	1246		
G2	2017	49	1	M	3	633	3073	672 ± 42	3184 ± 147
G2						716	3350		
G2						667	3128		
G1	2010	42	7	M	3	683	3475	657 ± 107	3320 ± 456
G1						716	3589		
G1						467	2526		
G1						722	3639		
G1						695	3369		
F2	2017	44	1	F	3	723	3446	639 ± 107	2939 ± 646
F2						779	3805		
F2						568	2484		
F2						527	2349		
F2						598	2609		
F1	2010	37	7	F	3	577	2685	643 ± 70	2932 ± 408
F1						567	2457		
F1						597	2579		
F1						719	3442		
F1						688	3244		
F1						711	3187		
H1	2010	38	7	F	3	622	3064	664 ± 39	3190 ± 115
H1						698	3290		
H1						671	3217		
H2	2017	45	1	F	3	522	2452	622 ± 105	3011 ± 628
H2						544	2479		

H2						527	2442		
H2						661	3267		
H2						748	3681		
H2						732	3745		
I2	2017	66	1	M	3	801	3504	773 ± 39	3513 ± 161
I2						730	3357		
I2						788	3679		
I1	1973	22	44	M	3	681	2398	700 ± 28	2353 ± 64
I1						720	2308		

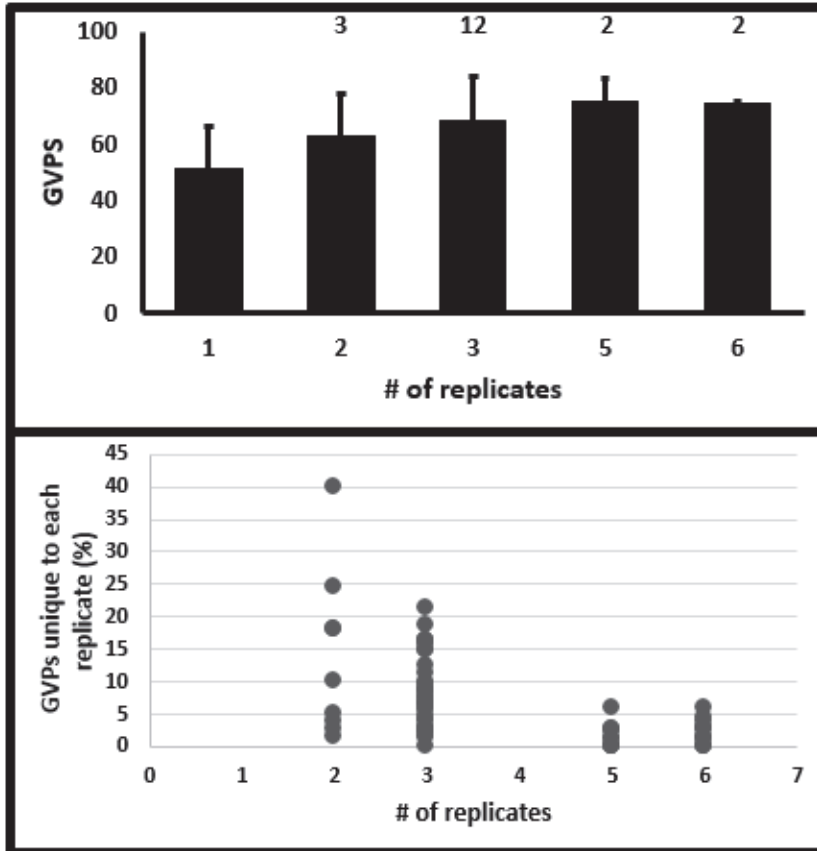


Figure S2. GVPs vs the number of replicates employed. The top panel presents the average number of GVPs identified vs the number of replicates used, while the bottom panel shows the percent GVPs unique to a replicate when 2, 3, 5 and 6 replicates were used. The number on the top of each bar indicates the number of different sample files analyzed for each scenario.

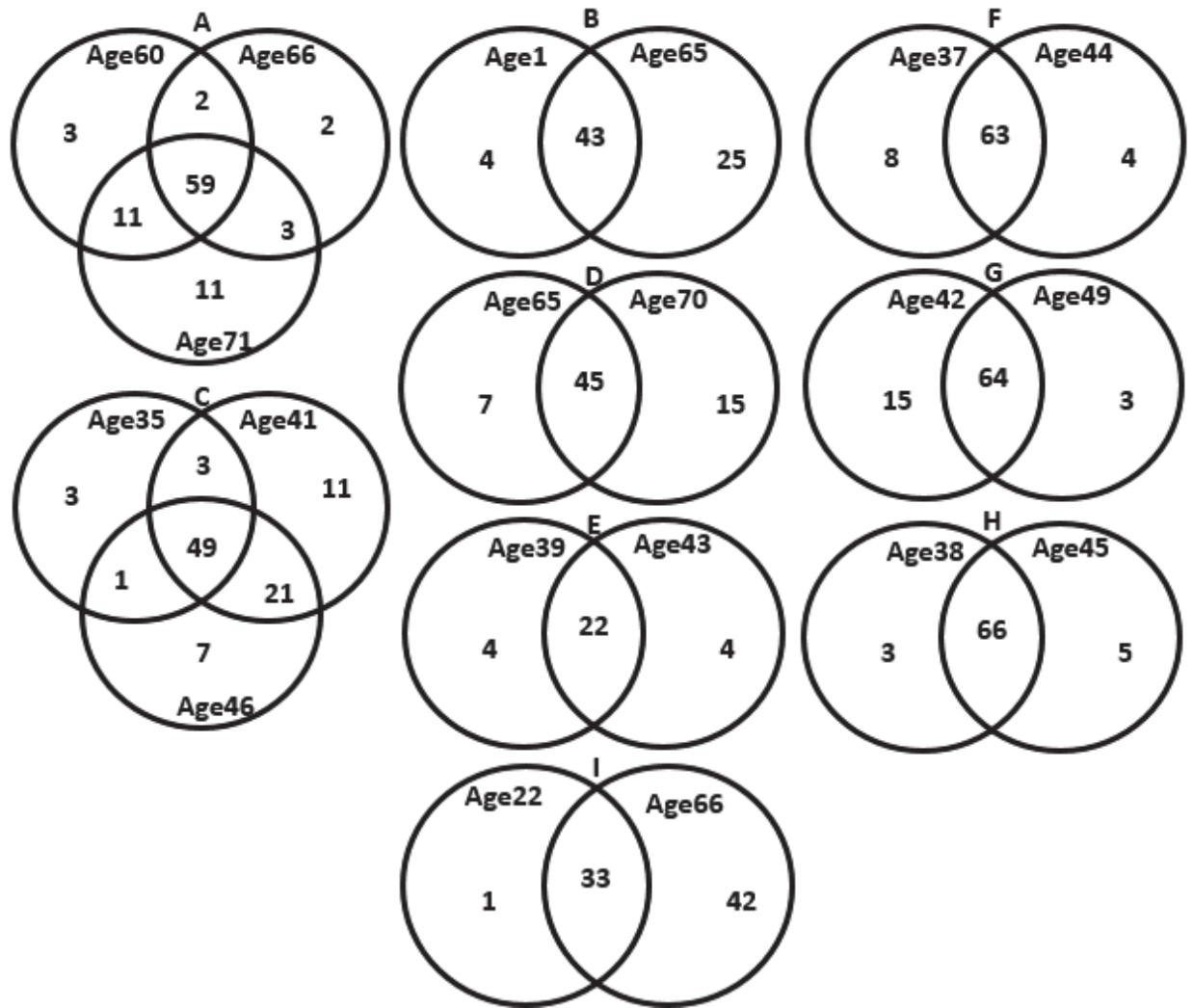


Figure S3. Number of GVPs common to samples at different ages or unique to a sample. Venn diagrams for each of the individuals are labeled on top of each diagram. The ages written at the tops of the circles represent ages of the individuals at the time of collection of samples.

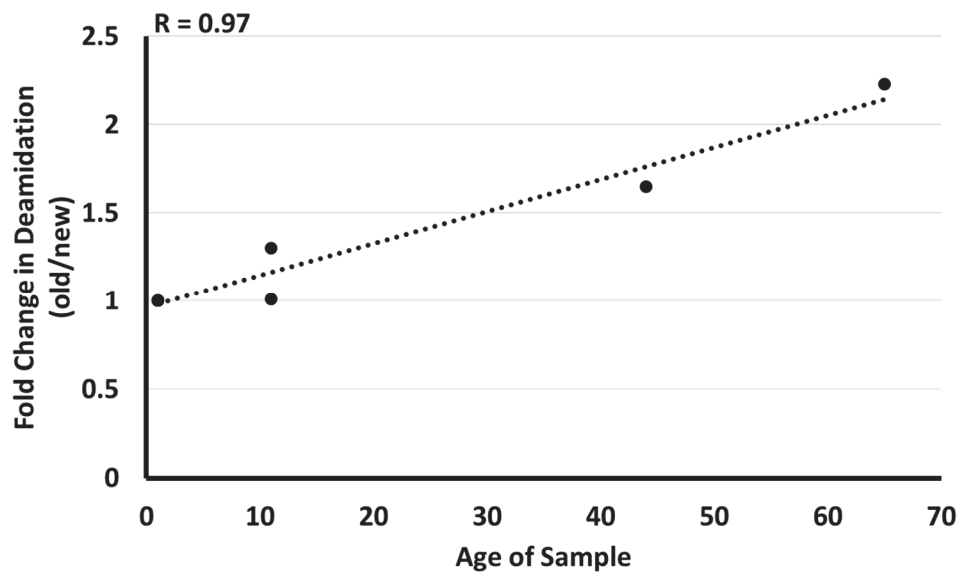


Figure S4. Deamidation of Q and N residues in proteins of hair samples stored for at least 10 years. Samples collected at different age points from individuals A, B, C and I were compared.

R code - Statistical Analysis - Age, Race

```
library(gdata)
library(edgeR)
library(dplyr)
library(RColorBrewer)

dat <- read.xls("WeightNotNorm-Ages.xls", stringsAsFactors = F, nrow = 261)
drop <- which(unlist(lapply(dat, function(x) all(is.na(x)))))
dat <- dat[,-drop]
anno <- dat[,1:4]

counts <- dat[,5:ncol(dat)]
rownames(counts) <- dat$Accession.Number

d <- DGEList(counts)
d <- calcNormFactors(d)

group <- unlist(lapply(strsplit(colnames(counts), split = ".", fixed = T),
                        function(x)x[1]))

mm <- model.matrix(~0 + group)
y <- voom(d, mm, plot = T)

fit <- lmFit(y, mm)

# A1 vs A2
contr <- makeContrasts("groupA2 - groupA1", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
```

```

tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
              Identified.Proteins)
write.csv(tmp2,file = "A2_v_A1.csv", row.names = F)

# B1 vs B2
contr <- makeContrasts("groupB2 - groupB1", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
              Identified.Proteins)
write.csv(tmp2,file = "B2_v_B1.csv", row.names = F)

# C1 vs C2
contr <- makeContrasts("groupC2 - groupC1", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
              Identified.Proteins)
write.csv(tmp2,file = "C2_v_C1.csv", row.names = F)

```

```
# A1 vs B1
contr <- makeContrasts("groupB1 - groupA1", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
               Identified.Proteins)
write.csv(tmp2,file = "B1_v_A1.csv", row.names = F)
```

```
# B1 vs C1
contr <- makeContrasts("groupC1 - groupB1", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
               Identified.Proteins)
write.csv(tmp2,file = "C1_v_B1.csv", row.names = F)
```

```
# A1 vs C1
contr <- makeContrasts("groupC1 - groupA1", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
```



```
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,  
              Identified.Proteins)  
write.csv(tmp2,file = "C1_v_A1.csv", row.names = F)
```

```
# A2 vs B2
```

```
contr <- makeContrasts("groupB2 - groupA2", levels = colnames(coef(fit)))  
tmp <- contrasts.fit(fit, contr)  
tmp <- eBayes(tmp)  
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")  
tmp2$Accession.Number <- rownames(tmp2)  
tmp2 <- left_join(tmp2, anno)  
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,  
              Identified.Proteins)  
write.csv(tmp2,file = "B2_v_A2.csv", row.names = F)
```

```
# B2 vs C2
```

```
contr <- makeContrasts("groupC2 - groupB2", levels = colnames(coef(fit)))  
tmp <- contrasts.fit(fit, contr)  
tmp <- eBayes(tmp)  
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")  
tmp2$Accession.Number <- rownames(tmp2)  
tmp2 <- left_join(tmp2, anno)  
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,  
              Identified.Proteins)  
write.csv(tmp2,file = "C2_v_B2.csv", row.names = F)
```

```
# A2 vs C2
```

```
contr <- makeContrasts("groupC2 - groupA2", levels = colnames(coef(fit)))  
tmp <- contrasts.fit(fit, contr)
```

```
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
              Identified.Proteins)
write.csv(tmp2,file = "C2_v_A2.csv", row.names = F)
```

```
#####
```

```
age <- substr(group, 1, 1)
```

```
mm <- model.matrix(~0 + age)
```

```
y <- voom(d, mm, plot = T)
```

```
fit <- lmFit(y, mm)
```

```
# A vs all B
```

```
contr <- makeContrasts("ageB - ageA", levels = colnames(coef(fit)))
```

```
tmp <- contrasts.fit(fit, contr)
```

```
tmp <- eBayes(tmp)
```

```
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
```

```
tmp2$Accession.Number <- rownames(tmp2)
```

```
tmp2 <- left_join(tmp2, anno)
```

```
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
              Identified.Proteins)
```

```
write.csv(tmp2,file = "B_v_A.csv", row.names = F)
```

```
# B vs all C
```

```
contr <- makeContrasts("ageC - ageB", levels = colnames(coef(fit)))
```

```
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
               Identified.Proteins)
write.csv(tmp2,file = "C_v_B.csv", row.names = F)
```

```
# A vs all C
contr <- makeContrasts("ageC - ageA", levels = colnames(coef(fit)))
tmp <- contrasts.fit(fit, contr)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
               Identified.Proteins)
write.csv(tmp2,file = "C_v_A.csv", row.names = F)
```

```
# MDS plot
cols <- brewer.pal(6, "Dark2")
tiff("MDS_age_race.tiff")
plotMDS(d, labels = group, col = cols[as.numeric(factor(group))])
dev.off()
```

```
# all 1 vs. all 2
race <- substr(group, 2, 2)
```

```
mm <- model.matrix(~race)
y <- voom(d, mm, plot = T)

fit <- lmFit(y, mm)

# A vs all B
tmp <- contrasts.fit(fit, coef = 2)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, n = Inf, sort.by = "P")
tmp2$Accession.Number <- rownames(tmp2)
tmp2 <- left_join(tmp2, anno)
tmp2 <- select(tmp2, Accession.Number, logFC, P.Value, adj.P.Val,
               Identified.Proteins)
write.csv(tmp2, file = "2_v_1.csv", row.names = F)
```

R code - Statistical Analysis - Individuals

```
library(gdata)

dat <- read.xls("ProfilesVsAge.xlsx", stringsAsFactors = F, skip = 1, nrow = 242, check.names = F)

dat2 <- dat
drop <- which(names(dat2) == "")
dat2 <- dat2[,-drop]
dat2[,5:73] <- lapply(dat2[,5:73], function(x)gsub(","," ", x, fixed = T))
counts <- data.matrix(dat2[,5:73])

library(edgeR)
d <- DGEList(counts)
d <- calcNormFactors(d)
rownames(d) <- dat$`#`

pdata <- read.xls("hair_aging_sample_info.xlsx", stringsAsFactors = F)
identical(pdata$sample, colnames(d))

# boxplot(d$sample$norm.factors ~ pdata$processed_by)

# Calculate batch-adjusted MDS plot
library(RColorBrewer)
cpms <- cpm(d, log = T)
resids <- t(apply(cpms, 1, function(x)resid(lm(x ~ processing_batch, data = pdata))))
cols <- c("black", brewer.pal(8, "Set2"))
tiff("./figures/MDS_batch_adjusted_by_subject_and_year.tiff", width = 8, height = 8, res = 400, units =
"in")
plotMDS(resids, col = cols[as.numeric(factor(pdata$subject))], labels = pdata$collection_year)
legend("right", text.col = cols, legend = levels(factor(pdata$subject)), title = "Subject")
```

```

dev.off()

tiff("./figures/MDS_batch_adjusted_by_subject_and_sample.tiff", width = 8, height = 8, res = 400, units
= "in")

plotMDS(resids, col = cols[as.numeric(factor(pdata$subject))], labels = colnames(cpms))
legend("right", text.col = cols, legend = levels(factor(pdata$subject)), title = "Subject")

dev.off()

# derive time since sample collection as 2017 - year, or 2018 - year if second batch
pdata$sampage <- ifelse(pdata$processed_by == "TJP", 2017 - pdata$collection_year,
                      2018 - pdata$collection_year)

# Derive hair sample
pdata$hair <- substr(pdata$sample, 1, nchar(pdata$sample) - 1)

# Set age to 1 if lt 1
pdata$collection_age <- ifelse(pdata$collection_age == "< 1", 1, as.numeric(pdata$collection_age))

#####
##### Analysis by time since sample was collected

mm <- model.matrix(~sampage + subject, data = pdata)
y <- voom(d, mm, plot = T)

#####

write.csv(cbind(rownames(y), dat$Accession.Number, y$E), file = "normalized_counts.csv", row.names =
F)

#####

```

```

# Calculate within-hair correlations

cor <- duplicateCorrelation(y, mm, block = pdata$hair)$consensus

fit <- lmFit(y, mm, block = pdata$hair, correlation = cor)

# Estimate contrasts

#year

tmp <- contrasts.fit(fit, coef = 2)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, sort.by = "P", n = Inf)
length(which(tmp2$adj.P.Val < 0.05))

anno <- dat[,1:4]
names(anno)[2] <- "Identified Proteins"

out <- merge(anno, tmp2, by.y = "row.names", by.x = "#")

out <- out[order(out$P.Value),c("Accession Number", "Identified Proteins", "MW", "logFC", "P.Value",
"adj.P.Val")]

write.csv(out, "Protein_Expression_by_Years_Since_Collection_Results_ALL_SAMPLES.csv", row.names
= F)

# Plot significant proteins by year

sigs <- rownames(tmp2)[which(tmp2$adj.P.Val < 0.05)]

f <- function(X){
  protein <- unlist(strsplit(dat$`Accession Number`[which(dat$`#` == X)], split = "|", fixed =
T)[[1]])[3]
  x <- as.numeric(y$E[X,])
  plotname <- paste0("./figures/", protein, "_ALL_SAMPLES.tiff")
  tiff(plotname, width = 8, height = 8, res = 400, units = "in" )
  plot(x ~ collection_year, main = protein, xlab = "Year", ylab = "Normalized Expression", data =
pdata)
}

```

```

        abline(lsfitt(pdata$collection_year, x), col = 2)
dev.off()
drop <- which(pdata$hair == "R")
        plotname <- gsub("_ALL_SAMPLES", "_NO_SAMPLE_R", plotname)
        tiff(plotname, width = 8, height = 8, res = 400, units = "in" )
        plot(x[-drop] ~ pdata$collection_year[-drop],
            xlab = "Year", ylab = "Normalized Expression", main = protein)
        abline(lsfitt(pdata$collection_year[-drop], x[-drop]), col = 2)
        dev.off()
}
sapply(sigs, f)

# Refit model without hair R
drop <- which(pdata$hair == "R")
mm <- model.matrix(~sampage + subject, data = pdata[-drop,])
y.no1951 <- voom(d[, -drop], mm, plot = T)
cor <- duplicateCorrelation(y.no1951, mm, block = pdata$hair[-drop])$consensus
fit <- lmFit(y.no1951, mm, block = pdata$hair[-drop], correlation = cor)
tmp <- contrasts.fit(fit, coef = 2)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, sort.by = "P", n = Inf)
length(which(tmp2$adj.P.Val < 0.05))
anno <- dat[,1:4]
names(anno)[2] <- "Identified Proteins"
out <- merge(anno, tmp2, by.y = "row.names", by.x = "#")
out <- out[order(out$P.Value),c("Accession Number", "Identified Proteins", "MW", "logFC", "P.Value",
"adj.P.Val")]
write.csv(out, "Protein_Expression_by_Years_Since_Collection_Results_NO_SAMPLE_R.csv", row.names
= F)

```



```

#####
#####
# Analysis by subject age at collection
mm <- model.matrix(~collection_age + subject, data = pdata)
y <- voom(d, mm, plot = T)

# Calculate within-hair correlations
cor <- duplicateCorrelation(y, mm, block = pdata$hair)$consensus

fit <- lmFit(y, mm, block = pdata$hair, correlation = cor)

# Estimate contrasts
#year
tmp <- contrasts.fit(fit, coef = 2)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, sort.by = "P", n = Inf)
length(which(tmp2$adj.P.Val < 0.05))
anno <- dat[,1:4]
names(anno)[2] <- "Identified Proteins"
out <- merge(anno, tmp2, by.y = "row.names", by.x = "#")
out <- out[order(out$P.Value),c("Accession Number", "Identified Proteins", "MW", "logFC", "P.Value",
"adj.P.Val")]
write.csv(out, "Protein_Expression_by_Subject_Age_at_Collection_Results_ALL_SAMPLES.csv",
row.names = F)

# Refit model without hair R
drop <- which(pdata$hair == "R")
mm <- model.matrix(~collection_age + subject, data = pdata[-drop,])

```

```

y.no1951 <- voom(d[, -drop], mm, plot = T)
cor <- duplicateCorrelation(y.no1951, mm, block = pdata$hair[-drop])$consensus
fit <- lmFit(y.no1951, mm, block = pdata$hair[-drop], correlation = cor)
tmp <- contrasts.fit(fit, coef = 2)
tmp <- eBayes(tmp)
tmp2 <- topTable(tmp, sort.by = "P", n = Inf)
length(which(tmp2$adj.P.Val < 0.05))
anno <- dat[, 1:4]
names(anno)[2] <- "Identified Proteins"
out <- merge(anno, tmp2, by.y = "row.names", by.x = "#")
out <- out[order(out$P.Value), c("Accession Number", "Identified Proteins", "MW", "logFC", "P.Value",
"adj.P.Val")]
write.csv(out, "Protein_Expression_by_Subject_Age_at_Collection_Results_NO_SAMPLE_R.csv",
row.names = F)

```

```

cor(pdata$collection_age, pdata$collection_year)

```

```

##### Pairwise contrasts between hairs, within each batch

```

```

mm <- model.matrix(~0 + hair, data = pdata)

```

```

y <- voom(d, mm, plot = T)

```

```

fit <- lmFit(y, mm)

```

```

# Estimate contrasts--pairwise comparisons of all hairs

```

```

samps <- unique(pdata$hair[pdata$processed_by == "TJP"])

```

```

nsamp <- length(samps)

```

```

out <- dat[, c("Accession Number", "Identified Proteins (467)", "MW")]

```

```

names(out)[2] <- "Identified Proteins"
nsig <- matrix(nrow = nsamp, ncol = nsamp)
for (i in 1:(nsamp - 1)){
  for (j in (i + 1):nsamp){
    cont <- paste("hair", samps[i], " - hair", samps[j], sep = "")
    contr <- makeContrasts(cont, levels = colnames(coef(fit)))
    tmp <- contrasts.fit(fit, contr)
    tmp <- eBayes(tmp)
    tmp2 <- topTable(tmp, sort.by = "none", n = Inf)
    nsig[i, j] <- nsig[j, i] <- length(which(tmp2$adj.P.Val < 0.05))
    names(tmp2) <- paste(names(tmp2), samps[i], "v", samps[j], sep = ".")
    out <- cbind(out, tmp2[,c(1,4,5)])
  }
}
samps <- unique(pdata$hair[pdata$processed_by == "RHR"])
nsamp <- length(samps)
out <- dat[,c("Accession Number", "Identified Proteins (467)", "MW")]
names(out)[2] <- "Identified Proteins"
nsig <- matrix(nrow = nsamp, ncol = nsamp)
for (i in 1:(nsamp - 1)){
  for (j in (i + 1):nsamp){
    cont <- paste("hair", samps[i], " - hair", samps[j], sep = "")
    contr <- makeContrasts(cont, levels = colnames(coef(fit)))
    tmp <- contrasts.fit(fit, contr)
    tmp <- eBayes(tmp)
    tmp2 <- topTable(tmp, sort.by = "none", n = Inf)
    nsig[i, j] <- nsig[j, i] <- length(which(tmp2$adj.P.Val < 0.05))
    names(tmp2) <- paste(names(tmp2), samps[i], "v", samps[j], sep = ".")
    out <- cbind(out, tmp2[,c(1,4,5)])
  }
}

```

```

}
}
rownames(nsig) <- colnames(nsig) <- samp$

library(openxlsx)
wb <- createWorkbook()
addWorksheet(wb, "Results of Pairwise Comparisons")
writeData(wb, "Results of Pairwise Comparisons", out)
posStyle <- createStyle(fontColour = "#006100", bgFill = "#C6EFCE")
pvalcols <- grep("adj", names(out))

sapply(pvalcols,function(x) conditionalFormatting(wb, "Results of Pairwise Comparisons", cols = x, rows
= 1:nrow(out),

                    rule = "<0.05", style = posStyle))

addWorksheet(wb, "Num Sig Comparisons")
writeData(wb, "Num Sig Comparisons", nsig, rowNames = T)
Sys.setenv(R_ZIPCMD="C:/Rtools/bin/zip")
saveWorkbook(wb, "Pairwise Comparisons Between Samples.xlsx", overwrite = TRUE)

#####
###

#####
###

# subject-time interaction
mm <- model.matrix(~sampage*subject, data = pdata)
y <- voom(d, mm, plot = T)

# Calculate within-sample correlations
cor <- duplicateCorrelation(y, mm, block = pdata$hair)$consensus

fit <- lmFit(y, mm, block = pdata$hair, correlation = cor)

```

```

# Estimate contrasts
f <- function(subject){
  if (subject == "A"){
    con <- "sampage"
  }else{
    con <- paste0("sampage + sampage.subject", subject)
  }
  contr <- do.call(makeContrasts, list(contrasts = con, levels = make.names(colnames(coef(fit))))))
  rownames(contr) <- colnames(coef(fit))
  tmp <- contrasts.fit(fit, contr)
  tmp <- eBayes(tmp)
  results <- topTable(tmp, sort.by = "none", n = Inf)[,c("logFC", "P.Value", "adj.P.Val")]
  names(results) <- paste(names(results), subject, sep = ".")
  return(results)
}
subs <- unique(pdata$subject)
out <- lapply(subs, f)

# Merge files
results <- do.call(cbind, out)
anno <- dat[,1:4]
out <- merge(anno, results, by.y = "row.names", by.x = "#")
library(openxlsx)
wb <- createWorkbook()
addWorksheet(wb, "Results")
writeData(wb, "Results", out)
posStyle <- createStyle(fontColour = "#006100", bgFill = "#C6EFCE")
pvalcols <- grep("adj", names(out))

```

```
sapply(pvalcols,function(x) conditionalFormatting(wb, "Results", cols = x, rows = 1:nrow(out),
          rule = "<0.05", style = posStyle))
Sys.setenv(R_ZIPCMD= "C:/Rtools/bin/zip")
saveWorkbook(wb, "Subject by Time Since Sample Collection Interaction Model.xlsx", overwrite = TRUE)
```

```
##### Plots of distances
```

```
cpms <- cpm(d, log = T)
```

```
resids <- t(apply(cpms, 1, function(x)resid(lm(x ~ processing_batch, data = pdata))))
```

```
d <- dist(t(resids), diag = T)
```

```
d2 <- as.matrix(d)
```

```
subs <- unique(pdata$subject)
```

```
nsub <- length(subs)
```

```
between.subject.dists <- NULL
```

```
between.subject.names <- NULL
```

```
within.subject.dists <- NULL
```

```
within.subject.names <- NULL
```

```
for (i in 1:nsub){
```

```
  for (j in 1:i){
```

```
    subject1 <- subs[i]
```

```
    subject2 <- subs[j]
```

```
    if (i == j){
```

```
      t1 <- which(pdata$subject == subject1)
```

```
      #
```

```
      tmp <- d2[t1, t1]
```

```
      tmp0 <- as.numeric(tmp[lower.tri(tmp)])
```

```

within.subject.dists <- c(within.subject.dists, tmp0)
pairname <- paste(subject1, subject1, sep = ".")
within.subject.names <- c(within.subject.names, rep(pairname, length(tmp0)))
} else{
t1 <- which(pdata$subject == subject1)
t2 <- which(pdata$subject == subject2)
tmp <- d2[t1, t2]
tmp0 <- as.numeric(tmp)
between.subject.dists <- c(between.subject.dists, tmp0)
pairname <- paste(subject1, subject1, sep = ".")
between.subject.names <- c(between.subject.names, rep(pairname, length(tmp0)))
}
}
}
names(within.subject.dists) <- within.subject.names
names(between.subject.dists) <- between.subject.names

avg.within.subject <- tapply(within.subject.dists, names(within.subject.dists),
function(x)sqrt(mean(x^2)))
avg.between.subject <- tapply(between.subject.dists, names(between.subject.dists),
function(x)sqrt(mean(x^2)))
tiff("./figures/Distance Boxplots.tiff", width = 8, height = 8, res = 400, units = "in")
boxplot(list(avg.within.subject, avg.between.subject), beside = T,
ylab = "Average Distance", xaxt = "n")
axis(1, at = 1:2, labels = c("Within Subjects", "Between Subjects"),line = 1, tick = F)
dev.off()

```