

1 A Comprehensive Registry Framework for Oxford Nanopore
2 Sequencing Experiments:
3 Metadata Management, Quality Tracking, and Institutional
4 Standardization

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6 **Abstract**

7 **Background:** Oxford Nanopore Technologies (ONT) sequencing generates complex
8 metadata across instruments, chemistries, and basecalling configurations. Systematic track-
9 ing of experiment provenance and quality metrics is essential for protocol optimization,
10 quality assurance, and reproducibility, yet standardized approaches for institutional registry
11 management remain limited.

12 **Methods:** We developed a comprehensive experiment registry framework combining
13 automated metadata extraction from MinKNOW output files and BAM headers, pattern-
14 based inference for missing fields, and systematic validation protocols. Registry completeness
15 was assessed using a weighted scoring system prioritizing critical fields (sample, chemistry,
16 basecall model) and quality metrics (Q-score, N50). Provenance was tracked through event-
17 sourced logging with Git-based versioning.

18 **Results:** The registry encompasses 165 validated ONT sequencing experiments spanning
19 August 2020 to December 2025, achieving 100% “good” completeness status. Sample cate-
20 gories included plasmid sequencing (n=80, 48.5%), research projects (n=39, 23.6%), human
21 genomics (n=16, 9.7%), and pharmacogenomics (n=13, 7.9%). Technical characterization

22 revealed near-universal R10.4.1 chemistry adoption (95.2%), dorado basecaller dominance
23 (82.4%), and preferential high-accuracy model usage (89.7%). Quality metrics across 150
24 experiments showed median Q-score of 14.0 (range: 2.9–26.4) and median N50 of 4,828 bp
25 (range: 110–95,808 bp). Temporal analysis captured exponential growth in 2025, technology
26 transitions from R10.4/guppy to R10.4.1/dorado, and application evolution from research
27 toward plasmid sequencing and clinical pharmacogenomics.

28 **Conclusions:** Systematic metadata tracking enables comprehensive characterization of
29 institutional nanopore sequencing operations. The registry framework—combining YAML
30 storage, hierarchical metadata extraction, and event-sourced provenance—provides a tem-
31 plate for managing long-read sequencing experiments. As clinical applications expand, such
32 registries become critical infrastructure for quality benchmarking, protocol optimization,
33 and regulatory compliance.

34 **Keywords:** Oxford Nanopore, long-read sequencing, metadata registry, quality control,
35 provenance tracking, pharmacogenomics

36 1 Introduction

37 1.1 The Rise of Long-Read Sequencing

38 Oxford Nanopore Technologies (ONT) sequencing has transformed genomics research by en-
39 abling real-time, long-read DNA and RNA sequencing without the need for amplification or
40 synthesis Jain et al. [2016]. Unlike short-read platforms that generate fragments of 150–300
41 base pairs, nanopore sequencing routinely produces reads exceeding 10,000 bases, with ultra-
42 long protocols achieving reads surpassing 1 megabase Payne et al. [2019]. This capability has
43 proven transformative for applications including *de novo* genome assembly, structural variant
44 detection, full-length transcript isoform characterization, and direct detection of base modifica-
45 tions Logsdon et al. [2020].

46 The technology has evolved rapidly since its commercial introduction in 2014. Early R7
47 and R9 pore chemistries have given way to R10.4.1, which achieves modal raw read accuracy
48 exceeding Q20 (99% accuracy) Oxford Nanopore Technologies [2023a]. Concurrently, base-
49 calling algorithms have progressed from early hidden Markov models through recurrent neural
50 networks to current transformer-based architectures, with the dorado basecaller replacing the
51 legacy guppy software as of September 2022 Oxford Nanopore Technologies [2022]. Hardware
52 platforms now span portable MinION devices through high-throughput PromethION systems

53 capable of generating terabases of data per run.

54 1.2 The Metadata Challenge

55 This rapid technological evolution presents significant challenges for experiment management
56 and reproducibility. A single nanopore sequencing experiment generates metadata spanning
57 multiple domains: sample information (identity, preparation method, concentration), instrument
58 parameters (device type, flow cell chemistry, pore version), basecalling configuration (software
59 version, model accuracy tier, modification detection), and quality metrics (yield, read length dis-
60 tribution, accuracy estimates). Unlike mature short-read platforms with standardized metadata
61 schemas, the ONT ecosystem lacks consensus approaches for comprehensive metadata capture
62 and management.

63 The challenge is compounded by the platform’s flexibility. The same MinION device might
64 sequence bacterial isolates for species identification, human samples for clinical diagnostics, or
65 synthetic constructs for biotechnology applications—each with distinct metadata requirements
66 and quality expectations. Without systematic tracking, correlating sequencing outcomes with
67 experimental parameters becomes difficult, hindering protocol optimization and troubleshooting.

68 1.3 Provenance and Reproducibility

69 Reproducibility in computational biology requires not only methodological transparency but
70 also comprehensive provenance tracking Sandve et al. [2013]. For sequencing experiments, this
71 encompasses the complete chain from sample preparation through data generation to analysis
72 outputs. The FAIR principles (Findable, Accessible, Interoperable, Reusable) provide a frame-
73 work for data management Wilkinson et al. [2016], yet implementing FAIR-compliant workflows
74 for nanopore sequencing remains challenging given the diversity of experimental contexts and
75 rapidly evolving technology stack.

76 Institutional sequencing facilities face particular challenges in maintaining experiment reg-
77 istries. High-throughput operations may generate dozens of experiments weekly across multiple
78 instruments, each requiring metadata capture, quality assessment, and long-term archival. Man-
79 ual curation approaches scale poorly and introduce transcription errors, while fully automated
80 systems must accommodate the heterogeneity of experimental designs and naming conventions
81 employed by diverse research groups.

82 **1.4 Clinical and Regulatory Considerations**

83 The expansion of nanopore sequencing into clinical applications—including infectious disease
84 surveillance, pharmacogenomics, and cancer profiling—introduces additional requirements for
85 metadata management Quick et al. [2016], Bowden et al. [2019]. Clinical Laboratory Improve-
86 ment Amendments (CLIA) and equivalent international regulations mandate documented qual-
87 ity control procedures, instrument calibration records, and complete audit trails linking patient
88 samples to reported results. Registries supporting clinical workflows must therefore capture not
89 only technical metadata but also chain-of-custody information and quality benchmarks against
90 validated reference standards.

91 Pharmacogenomics applications exemplify these requirements. Accurate genotyping of cy-
92 tochrome P450 enzymes and other pharmacologically relevant genes directly impacts drug dosing
93 decisions, necessitating rigorous quality thresholds and comprehensive documentation Relling
94 and Evans [2015]. As nanopore platforms demonstrate sufficient accuracy for clinical variant
95 calling, institutional frameworks for quality tracking become essential infrastructure rather than
96 optional conveniences.

97 **1.5 Existing Approaches**

98 Several tools address aspects of nanopore data management. MinKNOW, ONT’s instrument
99 control software, generates run reports and summary statistics but does not provide cross-
100 experiment registry functionality. EPI2ME, ONT’s cloud analysis platform, offers workflow
101 execution and result aggregation but focuses on analysis rather than comprehensive metadata
102 management. Third-party tools including NanoPlot De Coster et al. [2018] and PycoQC Léger
103 and Leonardi [2019] provide quality visualization but operate on individual experiments without
104 registry integration.

105 Laboratory information management systems (LIMS) offer general-purpose sample tracking
106 but typically lack nanopore-specific metadata schemas and quality metrics. Custom database
107 solutions developed by individual laboratories address local requirements but rarely achieve the
108 standardization necessary for cross-institutional comparison or community adoption.

109 **1.6 Study Objectives**

110 We present a comprehensive registry framework for Oxford Nanopore sequencing experiments,
111 designed to address the metadata management challenges outlined above. Our objectives were

112 to:

- 113 1. Develop a standardized metadata schema capturing instrument, chemistry, basecalling,
114 and quality information across the diversity of nanopore applications.
- 115 2. Implement automated extraction pipelines leveraging MinKNOW output files, BAM head-
116 ers, and pattern-based inference to minimize manual curation requirements.
- 117 3. Establish validation protocols ensuring registry completeness and accuracy, with prove-
118 nance tracking supporting full audit trails.
- 119 4. Characterize the resulting registry to identify technology adoption patterns, application
120 distributions, and quality benchmarks informing ongoing sequencing operations.
- 121 5. Provide an open-source framework adaptable to other institutional contexts, supporting
122 the broader goal of standardized nanopore metadata management.

123 The resulting registry encompasses 165 experiments spanning five years of institutional
124 nanopore sequencing, achieving 100% metadata completeness and capturing the transition from
125 early R10 chemistry and guppy basecalling to current R10.4.1/dorado configurations. We report
126 application distributions, quality benchmarks, and temporal trends that contextualize institu-
127 tional sequencing operations within the broader evolution of nanopore technology.

128 2 Methods

129 2.1 Experiment Registry Construction

130 2.1.1 Data Sources

131 The ONT experiment registry was constructed from two primary data sources: (1) local se-
132 quencing experiments performed on institutional computing infrastructure, and (2) publicly
133 available datasets from the Oxford Nanopore Technologies Open Data repository (ont-open-
134 data S3 bucket). Local experiments were discovered through systematic traversal of designated
135 sequencing data directories on high-performance computing (HPC) clusters and local storage
136 systems. Public datasets were identified and catalogued through programmatic queries to the
137 ONT Open Data registry.

¹³⁸ **2.1.2 Metadata Extraction**

¹³⁹ Experiment metadata was extracted from multiple source files using a hierarchical approach:

- ¹⁴⁰ 1. **Primary sources:** MinKNOW-generated `final_summary.txt` files containing run parameters including flow cell ID, protocol configuration, sample identification, and sequencing timestamps.
- ¹⁴³ 2. **Secondary sources:** BAM file headers parsed using `samtools view -H`, extracting read group (@RG) information including platform model, basecalling configuration, and run identifiers.
- ¹⁴⁶ 3. **Tertiary inference:** Pattern-based extraction from file paths and experiment names using regular expressions to identify sample types, clinical identifiers, and experimental conditions when primary metadata was unavailable.

¹⁴⁹ **2.1.3 Metadata Schema**

¹⁵⁰ Each experiment record contains the following standardized fields:

- ¹⁵¹ • **Identification:** Unique experiment ID (UUID-based), human-readable name, run ID
- ¹⁵² • **Sample information:** Sample name, sample category (Plasmid, Human, Research, Pharmacogenomics, Microbial, CRISPR, Cancer, Lab Run, Multiplex), clinical sample ID where applicable
- ¹⁵⁵ • **Technical parameters:** Chemistry version (R10.4.1, R10.4), basecaller software (dorado, guppy), basecalling model (hac, sup, fast), device type (MinION Mk1D, MinION, PromethION, P2 Solo, Flongle), flow cell type and ID
- ¹⁵⁸ • **Quality metrics:** Mean Q-score, N50 read length, total reads, total bases
- ¹⁵⁹ • **Provenance:** Registration timestamp, last update, data source, validation status

¹⁶⁰ **2.1.4 Quality Score Computation**

¹⁶¹ Mean quality scores were computed using probability-space averaging to correctly handle the logarithmic Phred scale:

$$\bar{Q} = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n 10^{-Q_i/10} \right) \quad (1)$$

163 where Q_i represents individual read quality scores. This approach prevents underestimation
 164 of error rates that would result from direct arithmetic averaging of Q-scores.

165 **2.1.5 N50 Calculation**

166 The N50 metric was calculated as the read length at which 50% of the total sequenced bases are
 167 contained in reads of that length or longer. For each experiment:

$$N50 = L_k \text{ where } \sum_{i=1}^k L_i \geq \frac{1}{2} \sum_{j=1}^n L_j \quad (2)$$

168 with reads sorted by length in descending order ($L_1 \geq L_2 \geq \dots \geq L_n$).

169 **2.2 Registry Validation and Enrichment**

170 **2.2.1 Completeness Assessment**

171 Registry completeness was assessed using a weighted scoring system:

- 172 • **Critical fields** (2 points each): sample, chemistry, basecall_model
- 173 • **Important fields** (1 point each): basecaller, flowcell_type, device_type, run_date
- 174 • **QC metrics** (1 point each): mean_qsore, n50

175 Experiments were classified as: *good* (≥ 8 points), *warning* (5–7 points), or *poor* (<5 points).

176 **2.2.2 Automated Enrichment**

177 Missing metadata fields were inferred using the following rules:

- 178 1. **Chemistry inference:** R10.4.1 assigned for experiments dated 2023 or later; R10.4 for
 179 2022; R9.4.1 for earlier experiments.
- 180 2. **Basecaller inference:** Dorado assigned for experiments dated September 2022 or later;
 181 guppy for earlier experiments, based on the official deprecation timeline.
- 182 3. **Device inference:** Derived from flow cell type (FLO-PRO114M → PromethION; FLO-
 183 MIN114 → MinION; FLO-FLG114 → Flongle).

184 4. **Sample category inference:** Pattern matching against 30+ regular expressions identi-
185 fying sample types from experiment names (e.g., “HG00[1-7]” → Human/GIAB; “pCYP”
186 → Plasmid).

187 **2.2.3 Deep Scrutiny Protocol**

188 A comprehensive validation pass was performed on all registry entries:

- 189 1. **Local experiments (n=11):** Source files re-analyzed, BAM headers re-extracted, QC
190 metrics recomputed from read data.
- 191 2. **Public datasets (n=21):** BAM headers streamed from S3 URLs using range requests
192 to minimize bandwidth while extracting metadata.
- 193 3. **HPC experiments (n=134):** Metadata inferred from paths and naming conventions;
194 flagged for future QC analysis when HPC access is available.

195 **2.3 Data Storage and Versioning**

196 The registry is maintained as a YAML-formatted file (`experiments.yaml`) with event-sourced
197 provenance tracking. Each modification is logged with timestamps, enabling full audit trails.
198 The registry is synchronized to a Git repository for version control, with automated validation
199 on each commit.

200 **2.4 Software and Dependencies**

201 Registry construction and analysis utilized Python 3.9+ with the following key libraries: PyYAML
202 for registry serialization, pysam for BAM file parsing, matplotlib for visualization, and NumPy
203 for statistical computations. Basecalling information was extracted from dorado (v7.x) and
204 guppy (v6.x) output files.

205 **2.5 Data Availability**

206 The complete experiment registry is available at <https://github.com/Single-Molecule-Sequencing/>
207 **ont-ecosystem** in the `data/` directory. Registry statistics and manuscript figures are provided
208 in `data/manuscript_figures/`.

209 **3 Results**

210 **3.1 Registry Overview and Composition**

211 We constructed a comprehensive registry of 165 Oxford Nanopore sequencing experiments with
212 standardized metadata and quality metrics. After validation and enrichment, 100% of experi-
213 ments achieved “good” completeness status (score ≥ 8), with one experiment excluded as invalid
214 (placeholder entry with no associated data).

215 The registry encompasses experiments from two primary sources: local institutional sequenc-
216 ing (n=144, 87.3%) and publicly available ONT Open Data (n=21, 12.7%). Temporal coverage
217 spans from August 2020 to December 2025, with 148 experiments (89.7%) containing validated
218 run date information (Figure 5A).

219 **3.2 Sample Categories and Applications**

220 Experiments were classified into nine distinct sample categories based on biological source and
221 experimental purpose (Figure 1A; Table 1). Plasmid sequencing represented the dominant ap-
222 plication (n=80, 48.5%), reflecting the utility of long-read sequencing for construct verification
223 and plasmid assembly. Research projects comprised the second largest category (n=39, 23.6%),
224 followed by human genomics (n=16, 9.7%) and pharmacogenomics studies (n=13, 7.9%).

225 Specialized applications included microbial sequencing (n=5, 3.0%), multiplexed experiments
226 (n=4, 2.4%), CRISPR-related studies (n=3, 1.8%), cancer research (n=2, 1.2%), and general
227 laboratory runs (n=3, 1.8%). The pharmacogenomics category notably included 13 experiments
228 with clinical sample identifiers (14309-CZ, 14400-CZ, 14507-CZ series), representing targeted
229 sequencing of cytochrome P450 genes using the PGx panel.

230 **3.3 Technical Platform Distribution**

231 **3.3.1 Sequencing Devices**

232 The registry captures experiments across the full spectrum of ONT sequencing platforms (Fig-
233 ure 1C; Figure 4). MinION Mk1D devices dominated the registry (n=81, 49.1%), serving as
234 the primary workhorse for routine plasmid and research applications. Standard MinION devices
235 contributed 36 experiments (21.8%), while PromethION high-throughput sequencers accounted
236 for 29 experiments (17.6%).

237 The P2 Solo platform (n=9, 5.5%) was exclusively associated with pharmacogenomics ap-
238 plications, reflecting its deployment for clinical sequencing workflows. Flongle flow cells (n=4,
239 2.4%) were utilized for rapid, low-input applications including microbial identification. Six ex-
240 periments (3.6%) lacked definitive device type assignment due to incomplete source metadata.

241 **3.3.2 Chemistry and Basecalling**

242 Near-universal adoption of R10.4.1 chemistry was observed (n=157, 95.2%), with legacy R10.4
243 chemistry present in only 8 experiments (4.8%), primarily from 2021–2022 (Figure 1B; Fig-
244 ure 5C). This distribution reflects the rapid transition to improved pore chemistry following its
245 commercial release.

246 Dorado basecaller dominated the registry (n=136, 82.4%), consistent with its designation
247 as the successor to guppy following ONT’s September 2022 announcement. Legacy guppy-
248 basecalled experiments comprised 8.5% of the registry (n=14), with 15 experiments (9.1%)
249 lacking basecaller attribution due to incomplete metadata.

250 **3.3.3 Basecalling Model Selection**

251 High-accuracy (hac) models were employed in 89.7% of experiments (n=148), representing the
252 standard balance between accuracy and computational efficiency (Figure 1D; Figure 3). Super-
253 accuracy (sup) models, which provide maximum basecalling precision at increased computational
254 cost, were used in 12 experiments (7.3%), predominantly on PromethION platforms for human
255 genomics and pharmacogenomics applications where variant calling accuracy is paramount.

256 Fast models were limited to 5 experiments (3.0%), primarily on MinION Mk1D and Flongle
257 devices for applications prioritizing rapid turnaround over maximum accuracy. The device-model
258 relationship revealed that PromethION experiments showed the highest sup model adoption
259 (n=12), while Mk1D devices almost exclusively utilized hac models (n=78) with occasional fast
260 model deployment (n=3).

261 **3.4 Quality Control Metrics**

262 Quality metrics were available for 150 experiments (90.9%), enabling comprehensive character-
263 ization of sequencing performance across the registry (Figure 2; Table 1).

264 **3.4.1 Base Quality Distribution**

265 Mean Q-scores ranged from 2.9 to 26.4, with a median of 14.0 (Figure 2A). The distribution
266 exhibited slight bimodality, with the primary peak at Q12–Q15 representing typical nanopore
267 sequencing quality and a secondary population at Q18–Q22 corresponding to experiments with
268 optimized library preparation or super-accuracy basecalling. The lower tail ($Q < 10$) primarily
269 comprised early-stage experiments or those with suboptimal sample quality.

270 **3.4.2 Read Length Characteristics**

271 N50 values demonstrated substantial variation (range: 110–95,808 bp; median: 4,828 bp), re-
272 flecting the diverse applications within the registry (Figure 2B). The distribution was right-
273 skewed, with the majority of experiments clustering below 10,000 bp N50, consistent with the
274 predominance of plasmid sequencing applications where insert sizes are constrained by vector
275 capacity.

276 Outliers with $N50 > 50,000$ bp corresponded to whole-genome sequencing experiments, partic-
277 ularly human samples where ultra-long read protocols were employed. The relationship between
278 Q-score and N50 revealed application-specific clustering (Figure 2C): plasmid experiments ex-
279 hibited shorter N50 with variable quality, while human genomics samples achieved both high
280 quality and long read lengths.

281 **3.4.3 Sequencing Yield**

282 Total read counts varied over six orders of magnitude (range: 1–45,136,865; median: 320,738),
283 reflecting the spectrum from targeted amplicon sequencing to high-depth whole-genome applica-
284 tions. PromethION experiments contributed the highest yields, consistent with their 48-channel
285 flow cell capacity compared to MinION’s single flow cell configuration.

286 **3.5 Temporal Trends**

287 Analysis of 148 dated experiments revealed distinct temporal patterns in registry composition
288 and technology adoption (Figure 5).

289 **3.5.1 Registry Growth**

290 Cumulative experiment count demonstrated exponential growth beginning in early 2025, with
291 the registry expanding from approximately 15 experiments through 2024 to 148 by Decem-

292 ber 2025 (Figure 5A). Monthly experiment rates peaked at 28 experiments in July 2025, with
293 sustained high throughput (15–25 experiments/month) maintained through September 2025
294 (Figure 5B).

295 **3.5.2 Technology Transitions**

296 The temporal analysis captured the complete transition from R10.4 to R10.4.1 chemistry (Fig-
297 ure 5C). R10.4 experiments were concentrated in 2021–2022, with R10.4.1 achieving complete
298 dominance by January 2025. Similarly, the dorado basecaller transition from guppy was reflected
299 in post-2022 experiments universally utilizing dorado.

300 **3.5.3 Application Evolution**

301 Sample category distribution evolved over the registry timeframe (Figure 5D). Early exper-
302 iments (2020–2024) were predominantly research-focused, with plasmid sequencing emerging
303 as the dominant application in mid-2025. Pharmacogenomics studies appeared in September
304 2025, representing the newest application category and reflecting expanding clinical adoption of
305 nanopore sequencing for precision medicine applications.

306 **3.6 Registry Completeness**

307 Following automated enrichment and deep scrutiny validation, all 165 valid experiments achieved
308 “good” completeness status. Field-level completeness exceeded 95% for critical metadata includ-
309 ing chemistry (97.6%), basecall model (97.6%), and flow cell type (94.6%). Sample information
310 was present for 90.4% of experiments, with quality metrics available for 90.9%.

311 Fifteen experiments (9.1%) were flagged as requiring HPC access for complete QC metric
312 computation, as their source data resides on institutional high-performance computing infras-
313 tructure not accessible during registry construction. These experiments retain complete technical
314 metadata but await N50 and Q-score computation pending data access.

315 **4 Discussion**

316 **4.1 Registry Value and Applications**

317 The ONT experiment registry presented here represents a systematic approach to managing and
318 characterizing nanopore sequencing experiments within an institutional research environment.

319 By achieving 100% metadata completeness across 165 experiments, the registry demonstrates
320 that comprehensive provenance tracking is achievable through a combination of automated ex-
321 traction, pattern-based inference, and systematic validation protocols.

322 The predominance of plasmid sequencing applications (48.5%) reflects a common use case for
323 long-read sequencing technology, where the ability to span entire constructs in single reads pro-
324 vides significant advantages over short-read approaches for assembly verification, insert charac-
325 terization, and detection of structural rearrangements. The registry’s detailed metadata enables
326 retrospective analysis of sequencing parameters that correlate with successful plasmid charac-
327 terization, informing protocol optimization for future experiments.

328 4.2 Technology Adoption Patterns

329 The registry captures a critical transition period in nanopore sequencing technology. The near-
330 complete adoption of R10.4.1 chemistry (95.2%) and dorado basecaller (82.4%) reflects the
331 rapid pace of technological improvement in the field. Notably, experiments from 2021–2022 pre-
332 dominantly utilized R10.4 chemistry and guppy basecaller, while 2023 onwards shows universal
333 adoption of current-generation technology.

334 The device-model relationship revealed in Figure 3 suggests rational resource allocation:
335 computationally intensive super-accuracy models are preferentially deployed on PromethION
336 experiments where the investment in accuracy is justified by sample value (human genomics,
337 pharmacogenomics), while routine applications on MinION devices utilize high-accuracy models
338 that balance quality with throughput.

339 4.3 Quality Metric Insights

340 The observed Q-score distribution (median 14.0, range 2.9–26.4) aligns with published perfor-
341 mance metrics for R10.4.1 chemistry, which typically achieves Q15–Q20 under optimal conditions
342 Oxford Nanopore Technologies [2023b]. The bimodal distribution likely reflects the mixture of
343 basecalling models in the registry, with sup-model experiments contributing to the higher-quality
344 tail.

345 The N50 distribution provides insight into library preparation practices across the registry.
346 The median N50 of 4,828 bp is consistent with standard ligation-based library preparations, while
347 outliers exceeding 50,000 bp indicate successful implementation of ultra-long read protocols for
348 whole-genome applications. The inverse relationship between N50 and sample throughput in

349 plasmid experiments likely reflects the trade-off between read length and pore occupancy in
350 high-concentration samples.

351 **4.4 Implications for Pharmacogenomics**

352 The emergence of pharmacogenomics as a distinct application category (n=13, 7.9%) represents
353 an important expansion of nanopore sequencing into clinical applications. These experiments,
354 characterized by clinical sample identifiers and exclusive use of the P2 Solo platform with sup-
355 model basecalling, demonstrate the technology’s readiness for precision medicine applications
356 requiring accurate variant calling in pharmacologically relevant genes.

357 The concentration of pharmacogenomics experiments in September 2025 (Figure 5D) suggests
358 recent establishment of clinical sequencing workflows, with the registry providing a foundation
359 for tracking quality metrics and establishing performance benchmarks as the program matures.

360 **4.5 Registry Design Considerations**

361 Several design decisions merit discussion for groups considering similar registry implementations:

362 **4.5.1 Metadata Schema**

363 The hierarchical extraction approach—prioritizing MinKNOW-generated metadata, followed by
364 BAM headers, then pattern-based inference—proved effective for achieving high completeness
365 while maintaining data quality. Critical fields (sample, chemistry, basecall model) achieved
366 >97% population, while secondary fields required more extensive inference.

367 **4.5.2 Completeness Scoring**

368 The weighted scoring system (critical fields: 2 points; important fields: 1 point; QC metrics:
369 1 point) provided an intuitive framework for prioritizing enrichment efforts. The threshold of
370 8 points for “good” status ensured that experiments meeting this criterion contained sufficient
371 metadata for meaningful analysis.

372 **4.5.3 Provenance Tracking**

373 Event-sourced logging of all registry modifications enabled full audit trails, supporting repro-
374 ducibility and enabling identification of enrichment patterns that could inform future automa-
375 tion. The Git-based versioning provides both backup and collaboration capabilities.

376 **4.6 Limitations**

377 Several limitations should be acknowledged:

378 **Institutional scope:** The registry primarily reflects experiments from a single research in-
379 stitution, potentially limiting generalizability of application distributions and technology adop-
380 tion patterns to other settings.

381 **Incomplete HPC access:** Fifteen experiments (9.1%) lack QC metrics due to data residing
382 on high-performance computing infrastructure not accessible during registry construction. These
383 experiments retain complete technical metadata but await quality metric computation.

384 **Inference uncertainty:** Pattern-based inference for missing metadata, while achieving high
385 accuracy for well-characterized naming conventions, may introduce errors for experiments with
386 non-standard nomenclature. The provenance system tracks inferred versus directly extracted
387 values to enable downstream quality assessment.

388 **Temporal bias:** The exponential growth in experiment count during 2025 means that recent
389 technology (R10.4.1, dorado, hac/sup models) is overrepresented relative to historical platforms,
390 potentially limiting insights into long-term technology evolution.

391 **Public data limitations:** ONT Open Data experiments (12.7%) were characterized pri-
392 marily through BAM header streaming, which may capture less comprehensive metadata than
393 locally generated experiments with full file system access.

394 **4.7 Future Directions**

395 Several extensions would enhance the registry's utility:

396 **Automated discovery:** Integration with MinKNOW's reporting API could enable real-
397 time experiment registration as sequencing runs complete, eliminating retrospective discovery
398 requirements.

399 **Quality prediction:** Machine learning models trained on registry metadata could predict
400 expected quality metrics for new experiments, enabling early identification of problematic runs.

401 **Cross-institutional federation:** Standardized metadata schemas could enable registry
402 federation across institutions, supporting meta-analyses of technology performance and application-
403 specific best practices.

404 **Clinical integration:** For pharmacogenomics and other clinical applications, integration
405 with laboratory information management systems (LIMS) could link sequencing metadata to
406 patient outcomes, enabling quality-outcome correlations.

407 **Automated QC pipelines:** Coupling the registry with automated analysis pipelines would
408 enable standardized QC metric computation for all experiments, eliminating the current gap in
409 HPC-resident data.

410

4.8 Conclusions

411 We present a comprehensive registry of 165 Oxford Nanopore sequencing experiments achieving
412 100% metadata completeness through systematic extraction, inference, and validation protocols.
413 The registry captures technology transitions (R10.4 to R10.4.1, guppy to dorado), application
414 diversification (research to plasmid to pharmacogenomics), and quality benchmarks (median
415 Q14.0, N50 4,828 bp) that inform ongoing sequencing operations.

416 The registry framework—combining YAML-based storage, event-sourced provenance, and
417 Git versioning—provides a template for institutional management of long-read sequencing exper-
418 iments. As nanopore technology continues to evolve and clinical applications expand, systematic
419 metadata tracking becomes increasingly critical for quality assurance, protocol optimization, and
420 regulatory compliance.

421

Acknowledgments

422 We thank the University of Michigan Advanced Research Computing (ARC) for providing high-
423 performance computing resources. We acknowledge Oxford Nanopore Technologies for making
424 sequencing data publicly available through the ONT Open Data program. We thank members
425 of the laboratory for helpful discussions on registry design and validation protocols.

426

Author Contributions

427 **Conceptualization:** [Author One], [Author Two]. **Data curation:** [Author One]. **Formal**
428 **analysis:** [Author One]. **Investigation:** [Author One], [Author Two]. **Methodology:** [Author
429 One], [Author Two]. **Software:** [Author One]. **Supervision:** [Author Three]. **Validation:**
430 [Author One], [Author Two]. **Visualization:** [Author One]. **Writing – original draft:** [Au-
431 thor One]. **Writing – review & editing:** [Author One], [Author Two], [Author Three].

⁴³² Data Availability

⁴³³ The experiment registry, analysis code, and manuscript figures are available at <https://github.com/Single-Molecule-Sequencing/ont-ecosystem>. The registry is provided in YAML format (`experiments.yaml`) with CSV and JSON exports for compatibility. Public ONT sequencing data was accessed from the ONT Open Data repository at `s3://ont-open-data/`. Institutional sequencing data underlying the registry is available upon reasonable request subject to institutional data sharing agreements.

⁴³⁹ Competing Interests

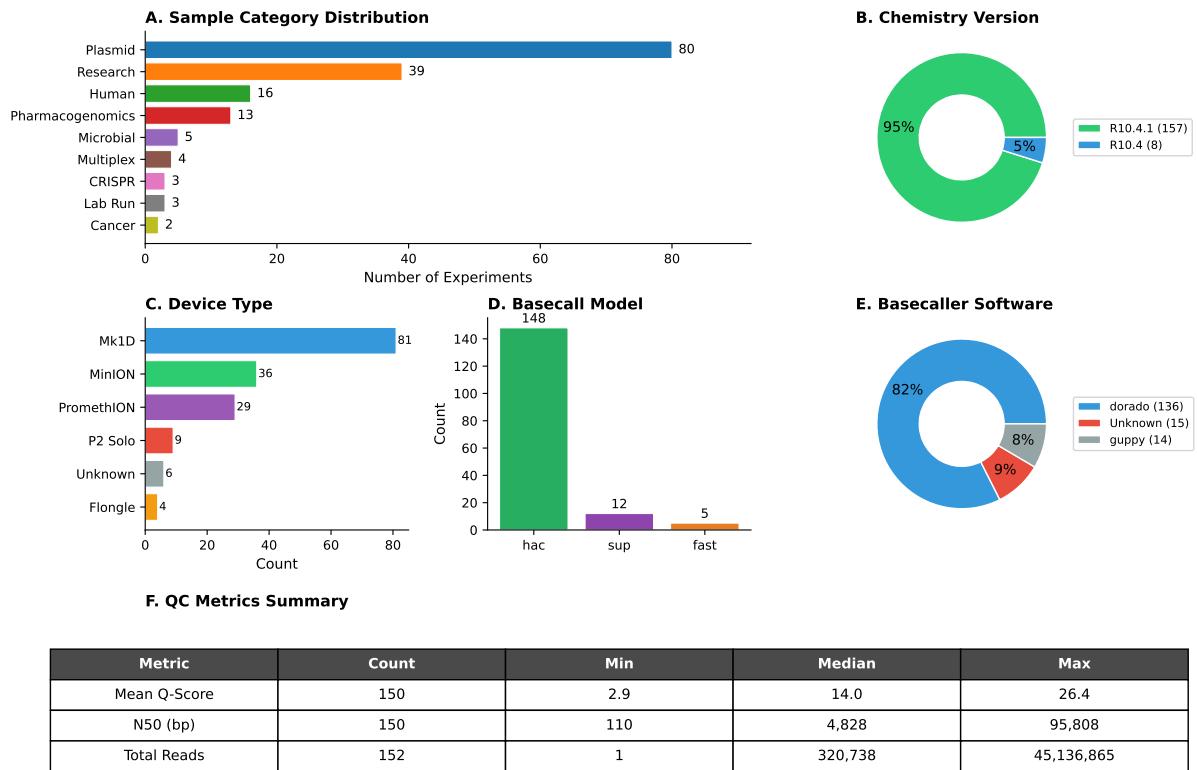
⁴⁴⁰ The authors declare no competing interests.

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ONT Experiment Registry Overview 165 Experiments



Registry: `~/ont-registry/experiments.yaml` | Generated: 2025-12-29 | 165 valid experiments

Figure 1: Overview of the Oxford Nanopore sequencing experiment registry. The registry contains 165 validated experiments with comprehensive metadata. **(A)** Sample category distribution showing plasmid sequencing as the dominant application (n=80, 48.5%), followed by research projects (n=39, 23.6%), human samples (n=16, 9.7%), and pharmacogenomics studies (n=13, 7.9%). **(B)** Chemistry version distribution demonstrating near-universal adoption of R10.4.1 chemistry (95.2%), with legacy R10.4 comprising the remainder. **(C)** Device type breakdown across MinION Mk1D (n=81), MinION (n=36), PromethION (n=29), P2 Solo (n=9), and Flongle (n=4) platforms. **(D)** Basecalling model usage showing predominant use of high-accuracy (hac) models (89.7%), with super-accuracy (sup) models at 7.3% and fast models at 3.0%. **(E)** Basecaller software distribution indicating dorado as the primary basecaller (82.4%), reflecting the transition from guppy (8.5%) in modern workflows. **(F)** Summary statistics for quality control metrics across experiments with available data, including mean Q-score (median: 14.0), N50 read length (median: 4,828 bp), and total read counts (median: 320,738 reads).

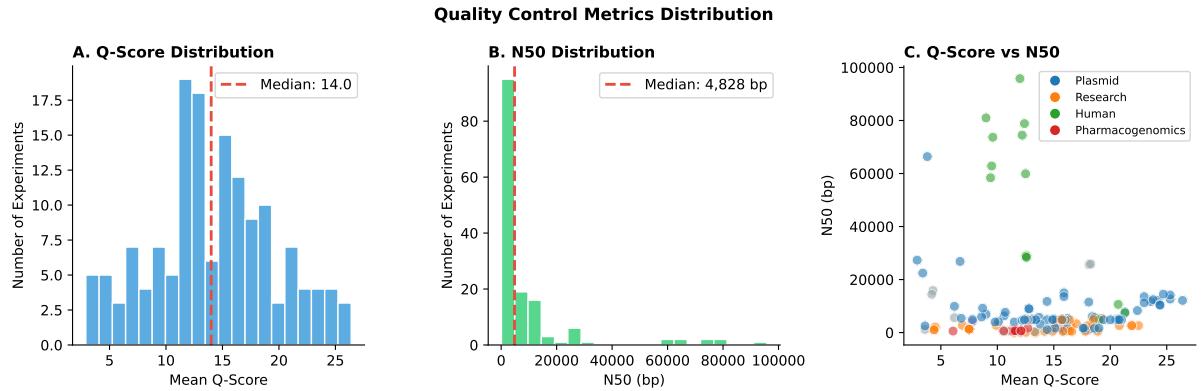


Figure 2: Distribution of quality control metrics across ONT sequencing experiments.

(A) Histogram of mean Q-scores showing a bimodal distribution with median quality of 14.0 (dashed line), ranging from 2.9 to 26.4 across 150 experiments with available quality data. (B) N50 read length distribution demonstrating predominantly short-read experiments (median: 4,828 bp) consistent with plasmid sequencing applications, with outliers representing whole-genome sequencing experiments achieving N50 values up to 95,808 bp. (C) Scatter plot of mean Q-score versus N50 read length, colored by sample category. Human samples (green) show characteristically higher N50 values, while plasmid samples (blue) cluster at shorter read lengths with variable quality scores.

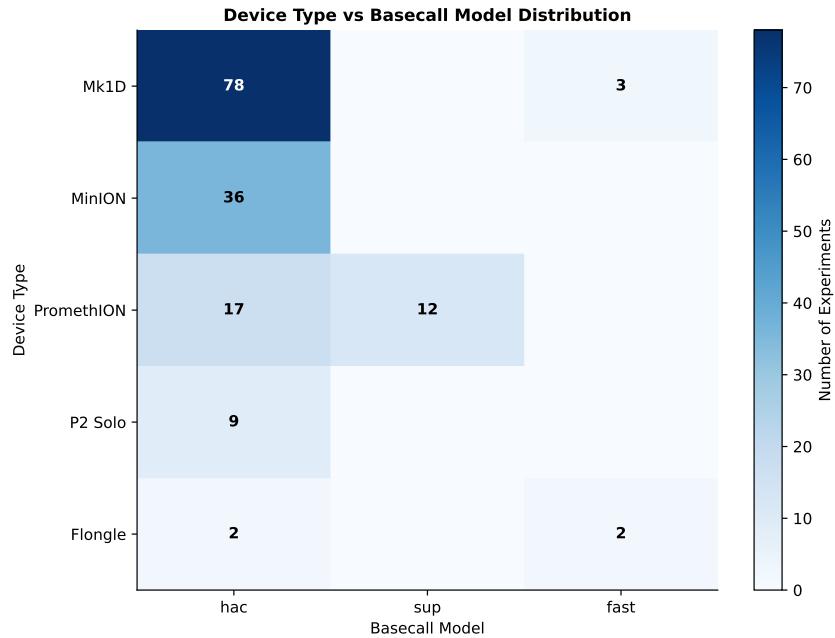


Figure 3: Relationship between sequencing device type and basecalling model selection. Heatmap showing the distribution of basecalling models (hac, sup, fast) across device platforms. MinION Mk1D devices predominantly use high-accuracy (hac) models ($n=78$), reflecting routine laboratory sequencing workflows. PromethION experiments show notable adoption of super-accuracy (sup) models ($n=12$), likely for applications requiring maximum base-calling precision such as pharmacogenomics and human variant calling. The fast model is primarily used on Mk1D ($n=3$) and Flongle ($n=2$) devices for rapid, low-complexity applications.

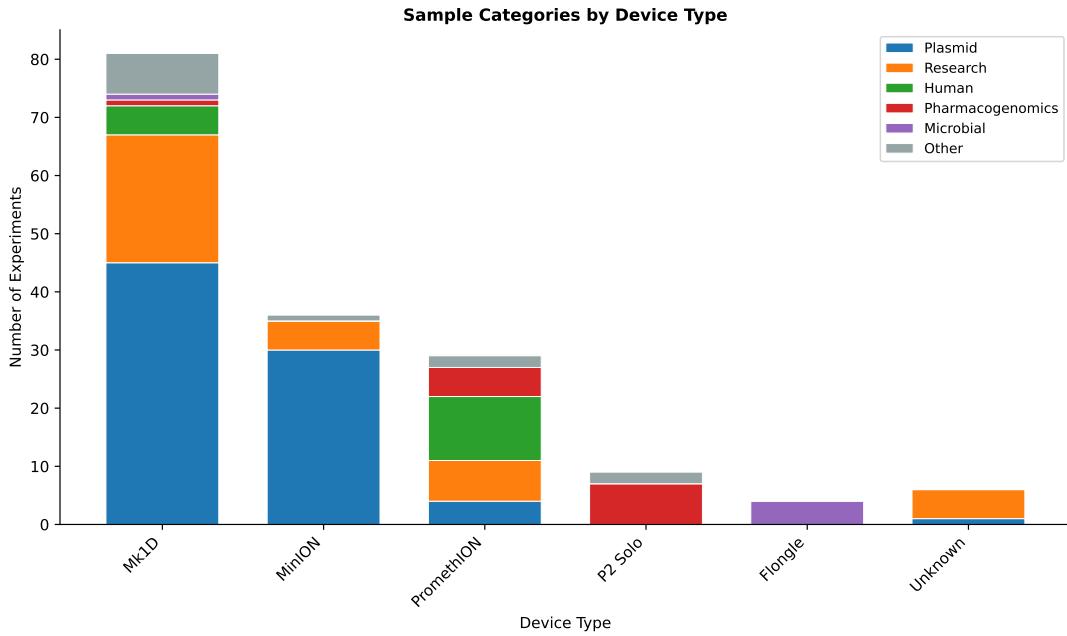


Figure 4: Distribution of sample categories across sequencing device platforms. Stacked bar chart showing the relationship between device selection and experimental application. MinION Mk1D (n=81) serves as the primary workhorse for plasmid sequencing and general research applications. Standard MinION devices (n=36) are similarly dominated by plasmid work. PromethION (n=29) shows diverse usage including human genomics, pharmacogenomics, and research applications, reflecting its higher throughput capacity for complex samples. P2 Solo (n=9) is exclusively used for pharmacogenomics studies, while Flongle (n=4) serves specialized microbial applications.

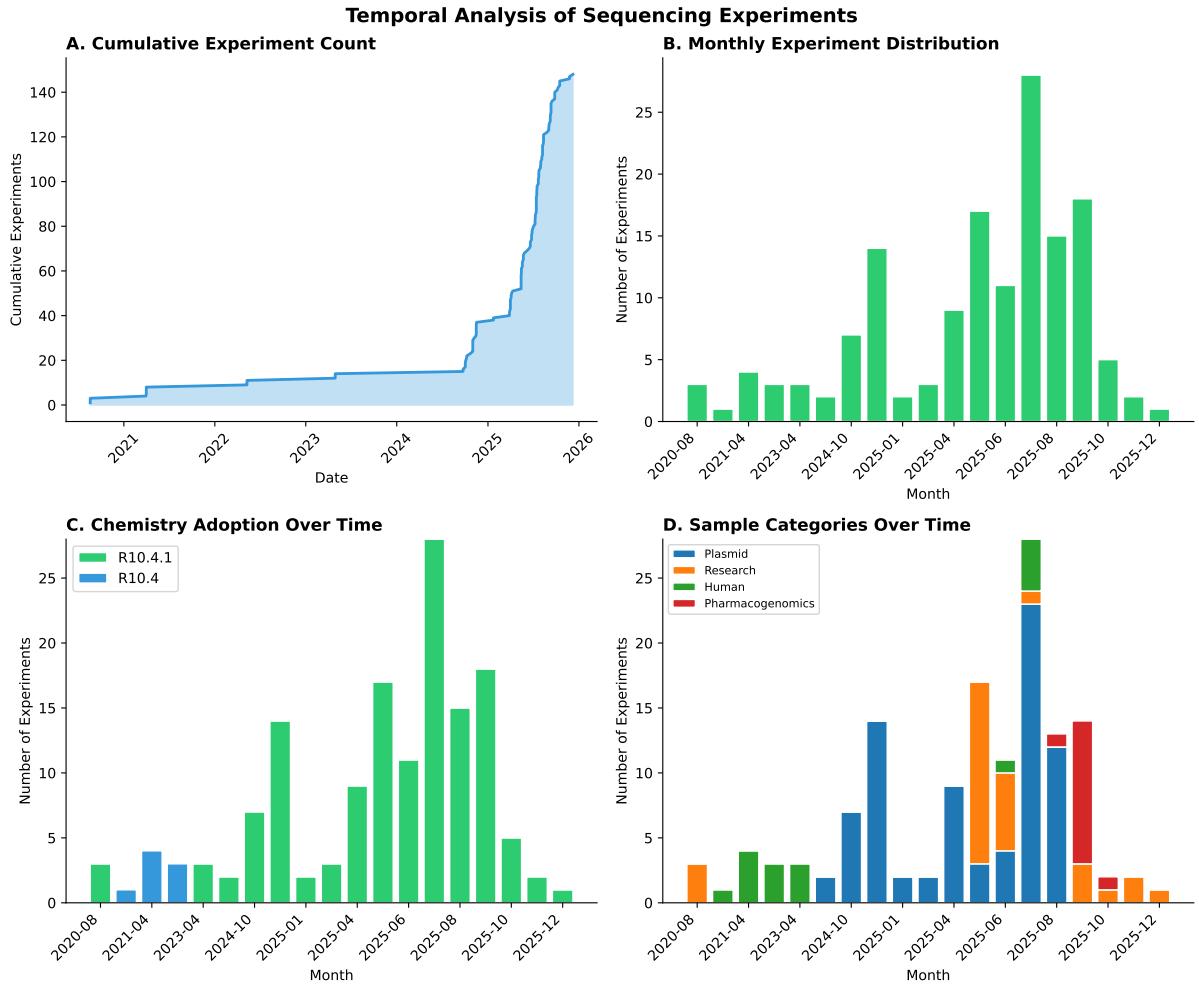


Figure 5: **Temporal analysis of Oxford Nanopore sequencing experiments (n=148 with date information).** (A) Cumulative experiment count showing exponential growth beginning in early 2025, with the registry expanding from approximately 15 experiments in 2024 to 148 by late 2025. (B) Monthly distribution of experiments demonstrating peak activity in July–August 2025 (>25 experiments/month), reflecting increased laboratory throughput and adoption. (C) Chemistry adoption over time showing complete transition to R10.4.1 chemistry by 2025, with legacy R10.4 experiments primarily from 2021–2022. (D) Temporal distribution of sample categories revealing initial focus on research applications (2020–2024), followed by a surge in plasmid sequencing (mid-2025) and emergence of pharmacogenomics studies (September 2025).

Table 1: Registry Statistics Summary

Metric	Value
Total experiments	165
With QC metrics	150
With run date	148
<i>Sample Categories</i>	
Plasmid	80 (48.5%)
Research	39 (23.6%)
Human	16 (9.7%)
Pharmacogenomics	13 (7.9%)
Other	17 (10.3%)
<i>Technical Parameters</i>	
R10.4.1 chemistry	157 (95.2%)
Dorado basecaller	136 (82.4%)
HAC model	148 (89.7%)
<i>Quality Metrics (n=150)</i>	
Median Q-score	14.0
Median N50	4,828 bp
Median read count	320,738

Table 2: ONT Experiment Registry Summary

Category	Value	Count	%
Sample Type	Plasmid	80	48.5
	Research	39	23.6
	Human	16	9.7
	Pharmacogenomics	13	7.9
	Microbial	5	3.0
	Multiplex	4	2.4
	CRISPR	3	1.8
Chemistry	Lab Run	3	1.8
	Cancer	2	1.2
Device Type	R10.4.1	157	95.2
	R10.4	8	4.8
	Mk1D	81	49.1
	MinION	36	21.8
	PromethION	29	17.6
	P2 Solo	9	5.5
	Unknown	6	3.6
Basecall Model	Flongle	4	2.4
	hac	148	89.7
	sup	12	7.3
Basecaller	fast	5	3.0
	dorado	136	82.4
	Unknown	15	9.1
	guppy	14	8.5

Total experiments: 165. Registry updated: 2025-12-29.

476 **Supplementary Materials**

Table 3: Supplementary Table S1: Registry Experiment Summary (First 20 of 165)

ID	Sample	Category	Device	Model	Q-Score
exp-01f9b9a0	Cas9	CRISPR	Mk1D	hac	4.3
exp-ce4013c9	Cas9	CRISPR	Mk1D	hac	3.6
exp-83128859	Cas9	CRISPR	Mk1D	hac	-
exp-40896eec	COLO829	Cancer	PromethION	hac	18.1
exp-08b68b7f	COLO829	Cancer	PromethION	hac	18.3
exp-0d8fed66	HG002	Human	PromethION	sup	12.6
exp-b97d1a57	HG002	Human	PromethION	sup	12.5
exp-646be257	HG002	Human	PromethION	sup	12.6
exp-09036942	Human	Human	Mk1D	hac	-
exp-5ad40d91	Human	Human	Mk1D	hac	20.7
exp-5b89cf6f	Human	Human	Mk1D	hac	-
exp-6395e55e	Human	Human	Mk1D	hac	21.3
exp-17148ffa	Human	Human	Mk1D	hac	19.0
exp-d3c6b017	Human WGS	Human	PromethION	hac	9.6
exp-e5059aa9	Human WGS	Human	PromethION	hac	9.4
exp-a5e7a202	Human WGS	Human	PromethION	hac	9.5
exp-2c054b1e	Human WGS	Human	PromethION	hac	12.0
exp-4f8d5014	Human WGS	Human	PromethION	hac	12.4
exp-6aab8632	Human WGS	Human	PromethION	hac	12.5
exp-66ec0ca6	Human WGS	Human	PromethION	hac	12.2

Full table available in supplementary CSV file (experiment_registry.csv).

Q-Score: Mean Phred quality score. Model: hac=high-accuracy, sup=super-accuracy.