
Enabling AI Safety Information Sharing: UK Competition Law Block Exemptions and Institutional Design

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Abstract

1 Frontier AI labs face a coordination failure: sharing safety-critical information
2 could prevent systemic failures, but competition law, designed to prevent collusion,
3 creates legal barriers to collaboration. This paper addresses this coordination failure
4 through comparative institutional analysis and legal framework redesign for the UK.
5 Drawing on cybersecurity (ISACs/ISAOs, CISA) and pharmaceutical (EudraVigilance)
6 precedents from the UK, EU, and US, we demonstrate how sector-specific
7 legal exemptions paired with neutral clearinghouse institutions resolve tensions
8 between competition enforcement and safety-critical information exchanges. We
9 develop a two-dimensional taxonomy that maps technical AI information by com-
10 mercial sensitivity and safety relevance, enabling clearinghouses and competition
11 authorities to weigh antitrust risk against safety value. Analysing UK Competition
12 Act Chapter I reveals that safety-critical information exchanges currently lack legal
13 clarity; most crucially, the existing R&D Block Exemption Order (2022) does not
14 protect post-deployment disclosures. Our analysis demonstrates that effective block
15 exemptions require three design principles: (1) FRAND access, (2) anonymisation
16 through neutral intermediaries, and (3) transparency requirements. We propose
17 establishing the UK AI Security Institute (AISI) as a neutral clearinghouse and sys-
18 tematically evaluate nine institutional mechanisms to incentivise AI lab information
19 sharing.

20 1 Introduction

21 Sharing information about model vulnerabilities and risk mitigation techniques could prevent systemic
22 AI failures, yet UK competition law lacks clarity on when such collaboration is permissible. Labs
23 sharing dangerous capabilities discoveries, red-teaming results, or safety protocols risk violating
24 Chapter I prohibitions of the Competition Act 1998, facing potential fines of up to 10% of worldwide
25 turnover for behaviour that serves public safety. This legal uncertainty persists despite widespread
26 recognition among researchers and industry that catastrophic AI failures could damage the entire
27 sector.

28 This paper examines how competing developers share safety-critical information about model vulner-
29 abilities, dangerous capabilities, and mitigation techniques without running afoul of competition law.
30 We focus on optimal collaboration in the UK context, where the Competition and Markets Authority
31 (CMA) has signaled increased scrutiny of AI foundation model markets while, at the same time, the
32 UK AI Security Institute (AISI) seeks to position itself as a global leader in AI safety research.

33 1.1 Contributions

34 This paper provides the first comprehensive legal analysis of competition law exemptions specifically
35 designed for AI safety information sharing in the UK context. Our three novel contributions are: (1)
36 a two-dimensional taxonomy mapping AI-specific information by commercial sensitivity and safety
37 relevance across model development stages (Section 3.2), (2) detailed application of UK Competition
38 Act Chapter I analysis to AI safety scenarios including a worked example of chain-of-thought sharing
39 (Section 3.3), and (3) concrete institutional design analysis establishing AISI as neutral clearinghouse
40 with systematic evaluation of nine complementary incentive mechanisms (Section 4). The legal
41 framework analysis and comparative evaluation represent entirely new empirical and analytical work
42 not present in prior publications.

43 1.2 The information sharing dilemma

44 Frontier AI developers' coordination problem has the characteristics of both a prisoner's dilemma and
45 a public goods provision challenge. Sharing critical safety information creates positive externalities:
46 all labs benefit from collective knowledge about risks to mitigate harmful tendencies and capabilities
47 of AI (bias, deceptiveness, the ability to support cyberattacks). However, several interrelated factors
48 discourage voluntary disclosure:

49 **Competition law uncertainty.** Information exchanges between competitors may trigger antitrust
50 scrutiny under the UK Competition Act 1998 Chapter I prohibitions. The legal boundaries are unclear
51 for AI safety information sharing because: (1) safety research often correlates with competitive
52 advantage, (2) information about model capabilities and timelines can signal market conduct even
53 when framed as safety disclosures, and (3) there is no precedent, and a lack of in-house technical
54 expertise, for how competition authorities should evaluate safety-motivated information sharing in
55 rapidly evolving technology sectors. Labs face significant legal risk including fines reaching up to
56 10% of turnover (1998).

57 **Competitive disadvantage.** A laboratory that invests millions in developing sophisticated evalu-
58 ation benchmarks or novel alignment techniques and shares these findings enables competitors to
59 incorporate insights at minimal cost, creating first-mover disadvantage.

60 **Liability exposure.** Disclosing safety issues creates documentary trails, establishing foreseeability in
61 future tort or criminal proceedings. Under UK law, liability for negligence requires demonstrating that
62 harm was foreseeable and reasonable precautions were not taken. By keeping information internal,
63 labs reduce the likelihood of legal action since potential claimants may lack evidence needed to
64 justify claims.

65 **Misaligned market incentives.** Current market structures reward capability advancement over safety
66 investment. Consumer purchasing decisions are driven by visible capabilities rather than safety
67 practices, creating weak market incentives for voluntary safety investments.

68 To locate solutions that weaken these disincentives, we examine how industries with similar char-
69 acteristics have historically shared information and attempted private governance. We analyse case
70 studies from cybersecurity for its vast technical information overlap, pharmaceuticals for its societal
71 recognition as a public good, and digital advertising for its twenty-first century emerging-industry
72 profile.

73 2 Precedents from safety-critical industries

74 As a sector, AI is new, large, dominated by limited major players, but still capable of sudden, rapid
75 evolution. Contemporary case studies provide insights from past antitrust challenges and the merits
76 of private or quasi-governmental governance structures.

77 2.1 Cybersecurity: ISACs, ISAOs and CISA

78 In 2001, nineteen U.S. high-tech companies formed the Information Technology Sharing and Analy-
79 sis Centre (IT-ISAC) following Presidential Decision Directive 63, which recognized that critical
80 infrastructure security would benefit from sharing cybersecurity risk information (1998). ISACs

81 exchanged threat intelligence in partnership with government agencies (DHS, FBI) but operated as
82 closed networks.

83 During the 2008-2009 Conficker worm crisis, the IT-ISAC mobilized major IT firms to share real-time
84 threat intelligence via anonymised channels, facilitating the sink-holing of millions of malicious
85 domains (2010). This demonstrated how voluntary, anonymised information sharing under strong
86 institutional governance can unify competing firms during collective risk. The UK currently lacks a
87 directly equivalent framework to CISA.

88 In 2015, Executive Order 13691 created ISAOs—flexible counterparts enabling any community to
89 form information sharing bodies with lower barriers to entry (2015).

90 That same year, the Cybersecurity Information Sharing Act (CISA) was enacted, providing three key
91 protection categories: **(1) Antitrust exemptions**—Section 104(E) establishes that sharing information
92 on threats or defences is not considered anti-competitive, and Section 106(B) provides that entities
93 sharing information are protected from antitrust liability; **(2) Liability protections**—companies
94 sharing cyber threat indicators in good faith receive liability shields; **(3) Confidentiality assurances**—
95 Section 105(D)(2) protects information shared with government as proprietary and not subject to
96 FOIA requests (2015). In 2018, CISA agency developed Automated Indicator Sharing (AIS) enabling
97 real-time exchange with anonymisation capabilities (2018).

98 **2.2 Pharmaceuticals: pharmacovigilance**

99 In the EU, the pharmaceutical sector shares safety information through European Medicines Agency
100 (EMA)-facilitated networks (2023). Companies must legally report adverse drug reactions to regu-
101 lators, who share findings industry-wide through EudraVigilance. This pharmacovigilance system
102 is hybrid: industry generates data while government (EMA’s Pharmacovigilance Risk Assessment
103 Committee) facilitates analysis and dissemination (2025). Because reporting is mandatory, com-
104 panies participate equally. EudraVigilance allows companies to see industry-wide safety trends
105 without exposing which competitor contributed which report. When serious risks are identified, all
106 manufacturers of similar drugs are alerted simultaneously.

107 Thus, in the EU’s pharmaceutical sector, patient safety trumps competitive secrecy: regulations ensure
108 critical risk information flows to all relevant parties. The precedent of regulated information-sharing
109 schemes (with legal mandates or incentives to report “adverse events” and incidents) may be effective
110 in balancing transparency and competition in other sectors.

111 **2.3 Digital advertising: self-regulation limits**

112 In the early 2000s, leading ad networks formed the Network Advertising Initiative (NAI) as a
113 self-regulatory trade association before formal privacy regulations. As voluntary initiative, NAI
114 avoided antitrust pitfalls by limiting collaboration to privacy and consumer protection, and receiving
115 endorsement from the Federal Trade Commission (2000). However, over time stronger U.S. state-
116 level laws emerged and NAI’s influence waned. This illustrates how industry-led governance can
117 buy regulatory goodwill and shape early norms, but decentralization can shift a trade association’s
118 external validation and legal reinforcement to remain credible.

119 As of March 2025, the Frontier Model Forum (FMF), a trade association that also sets pre-regulatory
120 safety standards, exists in a juxtaposed capacity to the NAI for digital advertising. Except that the
121 FMF is also only for members, who are presently only frontier AI firms. The NAI case study suggests
122 the FMF is valuable as governments catch up in learning how a new industry fits into the present
123 economy, but self-regulation becomes symbolic over time.

124 **3 Competition law analysis**

125 **3.1 UK legal framework**

126 The CMA possesses significant powers under the Competition Act 1998 to investigate and penalise
127 anti-competitive agreements falling into Chapter I prohibitions. The CMA’s April 2024 market
128 analysis focuses on AI foundation models, explicitly identifying risks of incumbent firms restricting
129 access to critical inputs. Existing frameworks like the R&D Block Exemption Order 2022 offer

130 potential routes for permissible collaboration, but applicability to AI safety information sharing is
 131 unclear. The primary barrier is the current absence of specific CMA guidance that explicitly clarifies
 132 which types of AI safety information sharing are considered low-risk.

133 **3.2 Information classification framework**

134 We develop a two-dimensional framework to classify frontier AI lab information by commercial
 135 sensitivity (CSI) and safety relevance across the pre-training/during training and post-deployment
 136 phases.

Table 1: Risk matrix: before/during training

	Low CSI	High CSI
Low Safety	Irrelevant	Proprietary datasets, Compute ownership
High Safety	Safety evaluation plans, Red team structures	Compute usage, Risk thresholds, Capabilities

Table 2: Risk matrix: after deployment

	Low CSI	High CSI
Low Safety	Irrelevant	Deployment timelines, Monetization
High Safety	Refusal accuracy, Jailbreak prevention	Red-teaming discoveries, Vulnerabilities

137 Information shared after deployment is generally less likely to qualify under R&D exemption and
 138 must be assessed with greater legal scrutiny.

139 **3.3 Technical challenges of generating and sharing types of information**

140 The technical challenges of generating safety-relevant information vary substantially across our
 141 classification framework (Tables 1-2). For high-safety, high-CSI information such as red-teaming
 142 discoveries or novel vulnerability identification, the primary challenge lies in capability elicitation.
 143 Ensuring that safety evaluations truly uncover the model’s dangerous capabilities, rather than merely
 144 testing what developers already know to look for, and preventing sandbagging of increasingly
 145 situationally aware models. Additionally, generating meaningful safety information about emergent
 146 capabilities requires extensive computing resources for comprehensive testing across diverse scenarios,
 147 specialised expertise in both AI systems and specific risk domains (CBRN, cybersecurity, autonomous
 148 weapons), and sophisticated instrumentation to detect subtle behavioural patterns that might indicate
 149 deceptive alignment or hidden capabilities. The generation challenge is compounded by the fact
 150 that as models become more capable, the search space for potential failure modes expands, and
 151 the time required for thorough safety evaluation may conflict with commercial pressures for rapid
 152 deployment. Furthermore, some types of information require technological innovation, such as
 153 jailbreaking prevention, redteaming structures or refusal accuracy.

154 Once safety-relevant information is generated, sharing it while preserving legitimate confidentiality
 155 and preventing competitive harm presents distinct technical challenges. Most safety technologies also
 156 give AI labs a competitive edge, which prevents information sharing. A technical platform where
 157 these safety and security issues and solutions can be shared without leakage would be helpful. Some
 158 vulnerabilities or jailbreaking methods might be model-specific which limits the effectiveness of
 159 information sharing. A neutral clearinghouse such as AISI could facilitate anonymisation and reduce
 160 legal uncertainty for participants.

161 **3.4 Case study: chain-of-thought sharing**

162 Three labs (A, B, C) develop advanced reasoning models with chain-of-thought capabilities and
 163 independently identify safety concerns by displaying reasoning traces. Raw traces contain: proprietary
 164 instructions/guardrails that could be reverse-engineered; technical vulnerabilities creating jailbreaking

165 attack surfaces; and exploitable edge cases. Labs want to share: (1) common structural standards for
 166 displaying sanitised reasoning, (2) intervention strategies for handling problematic traces, and (3)
 167 evaluation benchmarks for measuring trace quality/safety.

168 **Chapter I prohibitions assessment.** Information sharing must be assessed on whether it consti-
 169 tutes restriction "by object" (competitively sensitive information removing uncertainty between
 170 participants) or "by effect" (appreciable negative market impact).

171 *Structural standards* would not constitute restriction by object (no commercially sensitive strategies
 172 revealed) or by effect (standardization generally pro-competitive, encourages interoperability). *Inter-*
 173 *vention strategies* might be regarded as restriction by object (safety controls linked to commercial
 174 strategy/deployment plans) and by effect (may reduce independent decision-making on model release
 175 timing, triggering Section 2(2)(b) of Competition Act). *Evaluation benchmarks* would not qualify as
 176 restriction by object but may be restriction by effect depending on market structure.

177 **Section 9 exemptions assessment.** For exemption under Section 9, information sharing must: (1)
 178 promote technical progress/innovation, (2) allow consumers fair share of benefits, (3) not impose
 179 unnecessary restrictions, and (4) not eliminate competition.

180 *Structural standards* would likely qualify for exemption if voluntary and non-exclusive. *Intervention*
 181 *strategies* unlikely to qualify due to close connection to commercial strategies; labs must demonstrate
 182 information shared was reasonably necessary for pro-competitive gains. *Evaluation benchmarks* may
 183 qualify as sharing could lead to technical progress in safety measures with positive consumer pass-on.

184 3.5 Legal mechanisms for information sharing

185 Section 6 of Competition Act 1998 allows CMA to recommend to Secretary of State to establish
 186 exempt category of agreements. Where multiple similar agreements likely meet Section 9 conditions,
 187 CMA may recommend Block Exemption Order (BEO) providing ex-ante legal certainty.

188 The CMA's Guidance for Horizontal Agreements provides criteria: (1) Pro-competitive, (2) Necessary
 189 and proportionate, (3) Non-discriminatory (FRAND principles), (4) Aggregated or anonymised, (5)
 190 Exclude competitively sensitive information, (6) Voluntary and transparent, and (7) Third party acts
 191 as trustee.

Table 3: Comparison of legal mechanisms

Feature	Safe Harbor (via CMA Guidance)	Individual Exemption	Block Exemption
Legal Certainty	Medium-High: Strong comfort based on CMA enforcement intentions, but not absolute legal protection.	Low: Depends on robust self-assessment and evidence; if challenged, companies bear the burden of proof. Uncertainty is higher in novel/complex areas like AI.	High: Automatic exemption if the agreement strictly complies with all conditions. Provides highest legal certainty for compliant conduct.
Flexibility	Medium: Guidance can be principles-based but still sets defined parameters. More adaptable than a BEO.	High: Can apply to any bespoke AI safety sharing arrangement, tailored to specific needs.	Low: Agreement must conform strictly to the BEO's rules. Less adaptable to unique situations
Current Status	None for AI	Always available but high risk without specific guidance	None; requires government action

192 4 Institutional mechanism design

193 We evaluate nine policy options for incentivising information sharing, rated across feasibility, political
 194 will, and effectiveness (1-5 scale).

195 **4.1 Economic analysis of incentives**

196 Economic research offers quantitative insights into strategic dynamics. Gordon et al. (2003) and
197 Gal-Or and Ghose (2004, 2005) showed that security technology investments and information sharing
198 can function as strategic complements rather than substitutes. Strategic complementarity means that
199 the benefit to one firm of increasing its safety investment increases when other firms increase their
200 investments. This occurs when positive spillovers exist on either the **Demand side**—information
201 sharing increases overall market confidence or **Fixed-cost side**—shared information reduces fixed
202 costs (developing safety methodology, benchmarks, interpretability tools) rather than variable costs
203 (model-specific implementation).

204 Gal-Or and Ghose (2005) find that benefits increase with firm size and in more competitive industries.
205 Given AI development requires enormous capital and operates in an intensely competitive landscape,
206 leading AI labs could derive substantial benefits from structured information sharing. In sequential,
207 dynamic environments where companies observe others' contributions, the first firm committing
208 to sharing moves favorably for all firms, triggering positive cascades through the ecosystem. The
209 fixed cost channel seems more plausible for frontier AI than the demand side, as pre-training and
210 evaluations are fixed costs, while the evidence on demand estimation remains unclear. Since security
211 risks are not directly linked to the user, the user might not increase the overall demand much when
212 safer products enter the market.

213 **4.2 Why labs want (and don't want) to share**

214 **Incentives for sharing.** Researchers have genuine concern for safety, motivating labs to signal
215 commitments to attract safety-conscious talent (Odeh, 2021). Labs also cultivate regulatory goodwill
216 through voluntary safety collaboration, moderating regulatory intervention as seen in nuclear, chem-
217 ical, and aviation industries. Finally, collaboration strengthens relationships between researchers,
218 creating infrastructure for coordinated responses during potential AI safety crises.

219 **Disincentives for sharing.** Legal ambiguity creates costly friction, as evidenced by the current
220 practice of information sharing through lawyers. Sharing creates paper trails, exposing labs to future
221 liability (tort claims, criminal charges). First-mover disadvantage exists where costly safety research
222 becomes a public good benefiting competitors. Different labs have genuine disagreements over
223 priorities, danger thresholds, and risk assessments.

224 **4.3 Evaluation of nine mechanisms**

225 **1. Liability Shields** (Feasibility (F): 1.5, Political Will (PW): 2, Effectiveness (E): 4.5): Broader
226 shields beyond competition law protecting labs reporting to AISI from civil/criminal liability. Most
227 effective but requires legislative amendment. Precedents exist (Public Interest Disclosure Act 1998,
228 CISA Section 105).

229 **2. AISI as Clearinghouse** (F: 4, PW: 4, E: 4): AISI operates as a neutral third-party intermediary.
230 AISI's legal counsel designs protocols that aggregate and anonymise information to benefit safety
231 without enabling collusion. Requires Block Exemption Order approval but significantly reduces
232 antitrust concerns.

233 **3. IP Protections** (F: 4.5, PW: 3, E: 1.5): Patents for safety innovations. Light-touch but limited,
234 since patents limit the sharing of safety techniques. Royalty payments between labs would incentivise
235 safety innovations, but seem unlikely.

236 **4. AISI Lab Safety Scoring** (F: 4, PW: 3, E: 2.5): Certification system affecting lab reputation. This
237 may create adverse selection (labs selectively report positive information) and may damage AISI's
238 working relationships. These create public costs for labs that don't share information and offer labs a
239 way to get a good public reputation for sharing information privately.

240 **5. Safety Taxes** (F: 2, PW: 2, E: 3.5): Mandating risk mitigation when labs receive shared information
241 creates a compliance burden, incentivising sharing to slow competitors. But this may undermine
242 collaborative safety culture.

243 **6. Red-Team Bounty Pool** (F: Existing, PW: Existing, E: 3): AISI's existing program (£3,000-
244 £15,000 per submission). Pricing appropriately is difficult; without complementary liability shields,
245 labs may remain reluctant to report internally discovered vulnerabilities.

246 **7. Public Compute** (F: 5, PW: 3, E: 2): Compute access rewards. Highly feasible but limited
247 effectiveness due to scale disparity between public and private compute of advanced GPUs and other
248 AI chips such as TPUs.

249 **8. Public Liability Insurance** (F: 2.5, PW: 3, E: 2): Required insurance for AI harms. Insurance
250 industry lacks expertise to price AI risk. But labs are incentivised to withhold information to maintain
251 lower premiums.

252 **9. Private Governance** (F: 3.5, PW: 3, E: 2.5): AISI licenses private organizations as independent
253 certifiers, creating a competitive certification market. Consumer awareness not guaranteed; potential
254 race-to-laxest-certification.

255 **AISI as an arms-length body.** ALB status would enhance trust with labs reluctant to share with the
256 enforcer of the upcoming UK AI bill, more credibly maintain independence, and more easily attract
257 specialized talent. While AISI could theoretically function as a clearinghouse while remaining part of
258 DSIT, this might face greater challenges regarding trust and perceived neutrality. Whether the status
259 of an arm's-length body is sufficient to address Frontier Labs' concerns about sharing and exposing
260 information with the government remains to be seen.

261 **5 Discussion and policy implications**

262 Our analysis reveals three critical institutional design requirements for effective AI safety information
263 sharing frameworks. We frame these as analytical findings about necessary institutional features,
264 though policy implications are clear.

265 **5.1 Neutral clearinghouse institutions**

266 Our comparative analysis demonstrates that effective safety information sharing in competitive
267 markets benefits from neutral intermediary institutions that can aggregate, anonymise, and redistri-
268 bute information while maintaining both legal compliance and technical trust. Modeled after
269 EudraVigilance and ISAC/ISAO, which rely on trusted third parties to process sensitive information
270 by removing commercially identifying details while preserving safety value.

271 In the UK, AISI possesses the key characteristics of effective clearinghouses: established technical
272 credibility (with frontier labs) and recognized expertise, existing pre-deployment evaluation rela-
273 tionships, and government affiliation enabling regulatory coordination. Our analysis suggests three
274 necessary institutional capacities must be developed to move forward: (1) **in-house legal expertise**
275 **in UK competition law** to design information processing protocols maintaining compliance while
276 maximizing safety value, (2) **collaboration with the Competition Market Authority (CMA)** to
277 secure necessary legal frameworks, specifically block exemptions for post-R&D safety information
278 sharing that our Chapter I analysis (Section 3.3) demonstrates currently lacks legal clarity, and (3)
279 **technical infrastructure for sophisticated anonymisation** using privacy-preserving techniques
280 (differential privacy, secure computation, automated sensitive content detection).

281 This institutional model enables graduated information flows: highly sensitive discoveries shared
282 confidentially initially, moderately sensitive information redistributed after anonymisation, and
283 general safety insights disseminated broadly after appropriate time delays to incentivise innovation.
284 The clearinghouse transforms zero-sum competitive dynamics into positive-sum collaboration. It
285 reduces transaction costs through standardized procedures, creates accountability while maintaining
286 confidentiality, enables pattern detection across multiple reports, and provides government visibility
287 without requiring direct regulatory intervention that might chill innovation.

288 **5.2 Block exemption design principles**

289 To remedy the R&D Block Exemption Order 2022 that provides insufficient coverage for post-
290 deployment disclosures, AISI, in partnership with DSIT and the CMA, must work to establish a new
291 block exemption. Our analysis identifies three essential design principles for the redesign:

292 **(1) Precise scope definition**—Exemptions must explicitly cover both low-CSI/high-safety informa-
293 tion (safety evaluation plans, security protocols) and high-CSI/high-safety information (red-teaming

294 discoveries, deployment vulnerabilities) when shared through appropriate intermediaries, based on
295 our classification framework in Section 3.2.

296 **(2) Fair access (FRAND) governance**—Participation must remain voluntary, non-exclusive, and
297 open to all AI model developers and providers, both frontier and emerging, as defined by the CMA.
298 This remedies the negative effects of the "members-only" trade-association governance model that
299 cultivates cartel creation via exclusion (Section 2.3).

300 **(3) Transparency and adaptive governance**—Block exemptions should include CMA oversight
301 provisions, annual reporting on information sharing volumes (without disclosing confidential details),
302 and sunset clauses ensuring exemptions remain appropriate as AI markets evolve. Five-year review
303 periods with extension options would balance stability with adaptability.

304 Such block exemption would provide ex-ante legal certainty comparable to CISA’s antitrust protec-
305 tions, encouraging deeper collaboration on risk mitigation without chilling innovation. Our economic
306 analysis (Section 4) suggests this could catalyse positive cascades in information sharing through
307 strategic complementarity effects.

308 **5.3 Complementary incentive structures**

309 Legal clarity through block exemptions is necessary but insufficient. Even with reduced antitrust risk,
310 labs face economic barriers (first-mover disadvantage, free-riding) and psychological barriers (repu-
311 tation concerns, uncertainty about reciprocity) that discourage participation. Three complementary
312 approaches can address these remaining obstacles:

313 **(1) Reputational mechanisms** can provide low-cost signals of safety commitment. However, these
314 must be carefully designed to avoid adverse selection. Rather than scoring labs on safety outcomes
315 (incentivising selective disclosure of positive information only), effective systems would focus on
316 process metrics: frequency of participation, timeliness, and comprehensiveness. This aligns incentives
317 toward comprehensive rather than selective sharing.

318 **(2) Resource-based incentives** including compute credits, procurement preferences, or access to
319 national datasets can help offset first-mover costs. However, effectiveness depends critically on
320 resource value relative to private alternatives. For frontier labs with substantial private infrastructure,
321 public compute provides limited marginal value. More promising are unique government-held
322 resources (national datasets, procurement access) that labs cannot easily obtain through private
323 markets. Procurement only incentivises information sharing if public procurement is a meaningful
324 share of labs’ profit, which is not the case at the moment.

325 **(3) Experimental approaches** including regulatory sandboxes and pilot programs enable testing
326 protocols in controlled, lower-risk settings before scaling to industry-wide participation. Pilot
327 programs with 2-3 volunteer labs sharing information on specific challenges could demonstrate
328 viability, refine protocols, and build trust. This staged approach addresses coordination problems by
329 enabling first movers to demonstrate value.

330 Effectiveness likely depends on combination rather than any single mechanism. Labs face multiple
331 distinct barriers, and addressing only one may prove insufficient. A comprehensive approach com-
332 bining legal clarity (block exemptions), institutional infrastructure (neutral clearinghouse), positive
333 incentives (resource access), and experimental validation (pilot programs) addresses the multifaceted
334 coordination problem.

335 **5.4 Cross-sectoral legal architecture**

336 Our comparative institutional analysis reveals that effective frameworks require comprehensive legal
337 architecture addressing multiple liability categories simultaneously. The U.S. CISA model (Section
338 2.1) demonstrates how antitrust exemptions, liability protections, and confidentiality guarantees work
339 synergistically. Each protection addresses a distinct barrier: antitrust exemptions address competition
340 law uncertainty, liability protections address tort and criminal exposure, and confidentiality guarantees
341 address reputational concerns.

342 The UK currently lacks an equivalent comprehensive framework. While NIS Regulations 2018 and
343 the forthcoming Cyber Security and Resilience Bill establish mandatory reporting requirements,
344 they do not provide the triad of legal protections necessary for voluntary peer-to-peer information

345 sharing. Our analysis suggests that sector-agnostic legislation providing these protections for safety-
346 critical information sharing across multiple domains (cybersecurity, AI safety, critical infrastructure)
347 would create economies of scale in legal framework development and reduce perceptions of AI
348 exceptionalism.

349 The framework design should incorporate lessons from our institutional mechanism analysis. Effective
350 liability shields must protect good-faith disclosures from both civil claims and criminal exposure.
351 Clear antitrust exemptions must specify covered information categories and required conditions.
352 Confidentiality protections must guarantee that information shared through approved channels re-
353 ceives protection from public disclosure (FOIA exemption) and cannot be used in subsequent legal
354 proceedings against reporting entities (similar to CISA Section 105(D)(2)).

355 The framework should accommodate sector-specific clearinghouses (AISI for AI, ISACs for cyberse-
356 curity, potentially future bodies for biotechnology) while maintaining consistent core legal protections
357 across domains. This enables specialised technical expertise in each clearinghouse while providing
358 uniform legal certainty, potentially creating network effects as experience in one sector informs best
359 practices in others.

360 **6 Conclusion**

361 This paper addresses a fundamental AI governance challenge: enabling effective information sharing
362 on safety-critical issues while preserving competitive market dynamics. Through comparative
363 analysis of cybersecurity and pharmaceutical precedents, detailed examination of UK competition
364 law frameworks, and systematic evaluation of institutional mechanisms, we demonstrated viable
365 pathways for resolving this coordination failure.

366 Our analysis addresses three core frictions blocking AI safety information sharing. First, the lack of
367 trusted intermediaries—resolved through our design of AISI as a neutral clearinghouse with legal ex-
368 pertise, regulatory partnerships, and technical anonymisation infrastructure. Second, legal uncertainty
369 around antitrust—resolved through block exemption principles requiring precise scope definition,
370 FRAND access, and adaptive governance. Third, insufficient participation incentives—resolved
371 through complementary mechanisms addressing both economic barriers (first-mover disadvantage,
372 free-riding) and psychological barriers (reputation concerns, liability fears).

373 Together, these institutional innovations transform zero-sum competitive dynamics into positive-sum
374 safety collaboration. The classification framework, legal analysis, and mechanism evaluation provide
375 reusable tools applicable beyond the UK context. By demonstrating how thoughtful institutional
376 design can enable safety coordination without facilitating anticompetitive behaviour, this work charts
377 a path for AI governance that balances innovation, competition, and public safety.

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414 Cybersecurity Information.

415 **A Detailed analysis of institutional mechanisms**

416 **A.1 Liability shields**

- 417 **Feasibility (1.5/5):** Requires lobbying for amendment to UK legislation. Block exemption creates liability
418 exemptions for competition law but not for other liabilities (torts, criminal charges). Precedents: Public Interest
419 Disclosure Act 1998 (whistleblower protection); CISA Section 105(c)/(d) requires government keep shared
420 information secret; German Lieferkettensorgfaltspflichtgesetz where due diligence prevents automatic liability.
- 421 **Political Will (2/5):** Some political appetite exists. While introducing new legislation faces frictions, it is in
422 UK's interests to remain relevant in global AI development. Having foremost safety research institution with
423 collaborative relationships with leading labs is key advantage. Liability protections deepen relationships; AISI's
424 research talent helping technically helps UK get closer to US (desired geopolitical goal).
- 425 **Effectiveness (4.5/5):** Directly addresses common barrier. If AISI remains subject to oversight by government
426 regulator, labs may fear sensitive information could be disclosed or misused. Liability shield avoids this problem.
427 AISI can work with lab to help resolve issues. Second-order effect: cultivates trust, incentivising further sharing.
- 428 *Concerns:* Raises questions of fairness for potential AI damage victims who cannot pursue legal remedies.
429 Potential moral hazard where waiving legal consequences reduces incentives for proactive safety investment.
430 However, we envision this refers to proactive sharing during internal development/testing (pre-deployment), so
431 unlikely to be real external harms.

432 **A.2 AISI as information clearinghouse**

- 433 **Feasibility (4/5):** Key challenge is first needing Block Exemption Order approved by CMA and Secretary
434 of State. While we anticipate broad support, this represents significant administrative effort. Requires hiring
435 specialized competition law counsel and developing robust information filtering/anonymisation systems.
- 436 **Political Will (4/5):** Strong appetite anticipated. Gains all political advantages of Liability Exemptions with
437 minimal downside. More appealing if AISI not playing direct role in assisting frontier lab technical research,
438 making labs less dependent on foreign countries.
- 439 **Effectiveness (4/5):** Main advantage is government-attached neutral intermediary significantly reduces antitrust
440 concerns. AISI's legal team creates standardized procedures, removing commercially sensitive details while
441 preserving safety value. Companies want to share, but antitrust consequences are severe. Labs could rely on
442 AISI's well-designed process rather than navigating complex competition law individually.

443 Professional independence maintained: AISI’s legal counsel advises solely AISI on clearinghouse operations
444 while participating labs retain own independent counsel. This ensures compliance while reducing legal uncer-
445 tainty without creating attorney-client relationships compromising clearinghouse neutrality.

446 **A.3 Economic analysis expanded**

447 Strategic complementarity means benefit to one firm of increasing sharing/investment increases when other firms
448 increase theirs. However, this only occurs when positive spillovers exist on demand side (information sharing
449 increases overall market confidence, expanding demand for all firms) or fixed-cost side (shared information
450 reduces fixed costs like developing safety research methodology, benchmarks, interpretability/alignment tools
451 rather than variable costs like model-specific implementation, per-query safety techniques).

452 Without spillover effects, free-riding dominates. With complementarity, increase in one firm’s sharing induces
453 others to increase theirs, creating virtuous cycle. Particularly relevant to AI: Gal-Or and Ghose (2005) find
454 benefits increase with firm size and in more competitive industries. Given AI development requires enormous
455 capital and operates in intensely competitive landscape, leading labs could derive substantial benefits from
456 structured sharing.

457 While models examine single-shot simultaneous decisions, in sequential, dynamic environments like AI develop-
458 ment where companies observe others’ contributions, conclusion is more, not less, sharing. First firm committing
459 to sharing moves favorably for all firms, convincing entrant to follow suit, triggering positive cascades. This
460 improves opportunities for tacit collusion as increased sharing and technology investment lead to less aggressive
461 price competition, benefiting all participants with strictly higher profits under sequential than simultaneous
462 dynamics.

463 **A.4 Qualitative incentives and disincentives**

464 **Why labs want to share:** Researchers have genuine safety concern. This motivates labs (commercial entities) to
465 signal safety commitments to attract safety-conscious AI talent. Odeh (2021) found authenticity of commitments
466 critical in retaining motivated staff. Labs voluntarily signal safety care through collaboration to cultivate
467 regulatory goodwill, discouraging tighter regulation. Precedents in nuclear, chemical, aviation demonstrate
468 how voluntary safety collaboration moderates regulatory intervention. However, this requires industry-wide
469 collaboration—classic coordination problem where expected policy gains alone are insufficient incentives beyond
470 countervailing concerns. Labs want collaborative environment inspiring costly safety research; if shared as
471 public good, others free ride. Finally, collaboration strengthens pre-existing relationships, setting up formal
472 networks providing vital infrastructure for coordinated responses during potential AI safety crises.

473 **Why labs don’t want to share:** Legal ambiguity around information sharing between labs. Many safety-relevant
474 information kinds have less legal certainty regarding anti-competition laws. Source at frontier lab confirmed
475 current sharing is done via lawyers. In many cases, information like internal red teaming results not even useful
476 to share (not universal). Cost/usefulness asymmetry; costly and inconvenient process introducing collaboration
477 frictions.

478 Sharing information creates paper trail exposing labs to future liability. While we explored legal carve-outs
479 under competition law, these don’t shield from other liability forms (tort claims, criminal charges). Legal liability
480 often hinges on what company knew; disclosure makes establishing knowledge easier. Keeping information
481 internal reduces legal action likelihood since potential claimants may lack evidence to justify cases.

482 More inherent reason: first mover disadvantage where safety information, particularly techniques, are costly to
483 develop yet become public good when shared. Competitors access without granting sharer explicit reciprocal
484 benefit. We get unsustainable dynamics when not positive demand spillovers (consumer demand doesn’t
485 meaningfully increase with safety) or if safety sharing doesn’t reduce fixed costs (or reduces only variable costs).

486 Different researchers and labs have genuine disagreements over priorities, danger thresholds, risk assessments.
487 Differing standards over what constitutes meaningful safety concerns or acceptable risk means one party may
488 think sharing particular information unnecessary. Finally, certain information kinds have minimal sharing
489 incentive (specific model vulnerability exploitable). Addressing requires restricting model access and pausing
490 development, both costly.

Table 4: Cybersecurity Information Sharing Act (CISA) provisions

Provision	Allows/Requires	Legal Protections	Incentives
104(C)	Share cyber threat indicators with each other/government	Permitted for cybersecurity purposes	Voluntary collaboration
104(D)(1)	Security controls protecting against unauthorized access	Appropriate controls implemented	Shared info remains secure
104(D)(2)	Scrubbing personal data before sharing	Info anonymised for privacy	Balances transparency with privacy
104(E)	Sharing threat/defense info not anti-competitive	Antitrust exemption	Removes fear of legal action
105(D)(2)	Government-shared info protected as proprietary	FOIA exemption	Enables trust in government collaboration
106(B)	Entities sharing under 104(C) protected from antitrust liability	Liability protections	Reduces legal risk

491 **B CISA provisions**

492 **C Additional case study details**

493 **C.1 Pharmaceuticals extended**

494 Pharmaceutical sector benefits from industry-led trade associations (IFPMA, PhRMA) collaborating on global
 495 standards and best practices. Broader knowledge-sharing occurs at Drug Safety Symposium, CDISC Interchange,
 496 Reuters Events Pharma discussing pharmacovigilance methods, data standards, safety governance.

497 Legal safe harbors exist: in US, companies reporting problems through official channels when completing
 498 acquisitions are generally protected from some litigation consequences. As of 2018, EudraVigilance allows
 499 companies to see industry-wide safety trends without exposing which competitor contributed which report,
 500 preserving confidentiality and reducing duplicative reporting.

501 Pharma companies want to avoid negative publicity, so key challenge is ensuring sharing safety data doesn't
 502 become competitive disadvantage. Sector addresses this by aggregating and anonymising data. Adverse reaction
 503 reports (ICSRs) created by EMA don't name companies publicly; they feed into broader safety signals. When
 504 serious risk identified, all similar drug manufacturers alerted simultaneously. No single company unfairly singled
 505 out at early stage—focus is class-wide safety.

506 Industry engaged in pre-competitive collaborations. Firms pooled data on drug toxicology and early clinical trials
 507 to improve safety assessments for all, under consortia agreements protecting proprietary details. Collaborations
 508 with neutral coordinator (public-private partnership, professional association) help each company learn from
 509 others' failures without fearing immediate commercial fallout.

510 **C.2 Digital advertising extended**

511 Frontier Model Forum (FMF), founded by OpenAI, Anthropic, Google DeepMind, Microsoft, later joined by
 512 Amazon and Meta, has emerged as most visible framework for coordinating AI safety information sharing
 513 (March 2025). FMF positions itself as facilitator of cross-firm communication on safety risks, organizing efforts
 514 around: "vulnerabilities, weaknesses, and exploitable flaws;" "threats;" "capabilities of concern." However, FMF
 515 currently limited to members, leaving smaller/independent AI companies excluded.

516 FMF rise reflects common trend where trade associations lead early coordination before regulation catches
 517 up. Useful parallel: NAI helped set standards in online data collection later codified into law. While NAI not
 518 ultimately successful delivering strong, lasting privacy protections (compared to GDPR), it remains valuable
 519 case study in early self-regulation. Illustrates how industry facing political pressure and low public trust can
 520 coordinate to delay or shape upcoming regulation.

521 As voluntary initiative, NAI avoided antitrust pitfalls by limiting collaboration to privacy/consumer protection,
 522 not pricing or market division. FTC endorsement lent legitimacy, helped delay formal regulation. While no
 523 explicit legal immunity existed, transparency and public standards focus kept initiative within legal bounds. By
 524 agreeing baseline privacy rules, firms aimed preventing race to bottom for aggressive data practices provoking
 525 sector-wide backlash.