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OBSERVATIONAL COLLAPSE AND THE GRANULARITY-COVERAGE TRADE-OFF IN PRIVACY-CONSTRAINED MEASUREMENT SYSTEMS

Between 2018 and 2024, a sequence of regulatory and technical interventions fundamentally altered the conditions under which digital measurement systems operate. The General Data Protection Regulation (GDPR) [1], the California Consumer Privacy Act (CCPA/CPRA) [2], and Apple's App Tracking Transparency framework (ATT) [3] produced what Ivitskiy [4] terms observational collapse: a rapid, structural reduction in the fraction of an economic process that a measurement system can directly observe. ATT opt-in rates stabilized below 25 % [5], eliminating deterministic cross-application tracking for roughly 75 % of iOS users. Google's Privacy Sandbox initiative signals a parallel trajectory for the Android ecosystem. Industry estimates place attributable data loss at 30 % to 60 % [6]. The phenomenon extends well beyond advertising; any public monitoring system reliant on individual-level digital observation, from tax compliance analytics to healthcare utilization tracking and transportation demand estimation, faces the same structural constraint. This paper formalizes the resulting measurement trade-off and examines its consequences for the design of measurement systems in privacy-constrained environments.

The core quantity is the observability parameter $\omega(t) = \mathrm{Cobserved}(t) / \mathrm{Ctrue}(t)$, defined as the ratio of directly measured events to actual events [4]. Prior to 2018, measurement systems operated with $\omega(t)$ in the range of 0.80 to 0.95; that is, 80 % to 95 % of relevant events were directly observable. By 2024, this parameter had declined to 0.40 to 0.70 and continues to fall. The decline is not a temporary engineering problem amenable to technical fixes. It reflects deliberate policy choices by regulators and platform operators to restrict information flows, and the direction of these choices is unlikely to reverse. The parameter captures the degree of epistemic access a measurement system retains after privacy constraints are applied, and its trajectory determines the feasibility of any downstream inference.

A fundamental trade-off operates between measurement granularity and measurement coverage, structurally analogous to the Heisenberg uncertainty principle [7]. Ivitskiy [4] formalizes this as $\sigma g \cdot \sigma c \geq \kappa$, where σg is granularity uncertainty, σc is coverage uncertainty, and κ is a lower bound set by the prevailing regulatory regime. User-level tracking (low σg) triggers privacy controls that reduce the observable population (high σc). Aggregate reporting (high σg) preserves coverage but destroys individual-level signal. As κ increases, the feasible operating region shrinks and designers face increasingly sharp choices.

The empirical trajectory traces three distinct regimes. Under pre-2018 conditions ($\kappa 1$), systems achieved both high granularity and high coverage simultaneously. GDPR and CCPA ($\kappa 2 > \kappa 1$) forced a sacrifice of either individual precision or population completeness. The post-ATT regime ($\kappa 3 > \kappa 2$) pushed operating points to a region where meaningful individual-level tracking is infeasible for the majority of the observed population. Each tightening did not merely reduce data volume; it altered the kind of information available, qualitatively changing the inferential problem.

The information-theoretic consequences are direct. Following Shannon [8], effective channel capacity $\mathrm{Ceff}(t) = B(t) \cdot \log 2(1 + S(t)/N(t))$ declines as observational collapse reduces signal power $S(t)$ and increases noise $N(t)$ through platform-imputed data carrying unknown bias [4]. Cover and Thomas [9] established through the data processing inequality that no downstream analytical method can compensate for degraded input; a simple model on clean data outperforms a complex model on corrupted data [10]. Platforms compound this by filling observational gaps with modeled estimates $M(t)$, presenting $R(t) =$

$C_{observed}(t) + M(t)$ without distinguishing measured from imputed components. The modeling error $\varepsilon(t)$ is inaccessible to external observers, creating epistemic risk: optimization against a potentially distorted objective with no independent calibration [4].

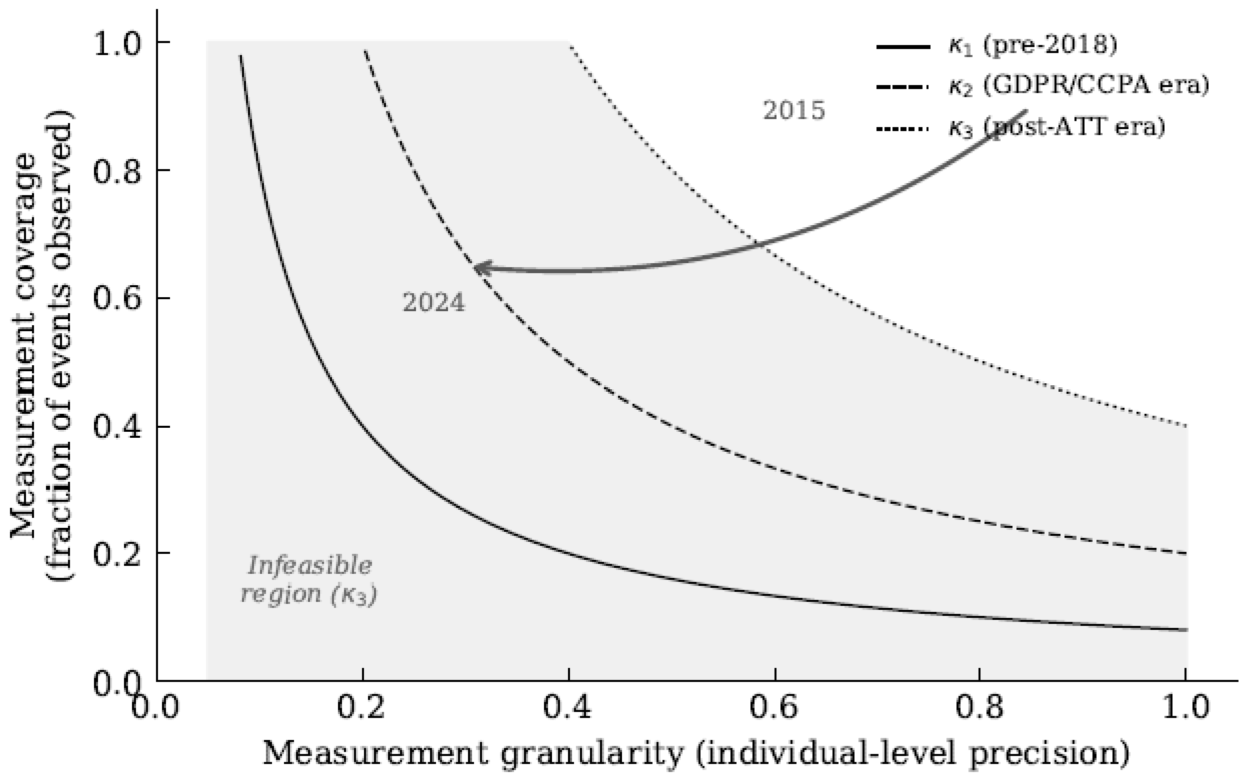

Figure 4. Granularity-coverage trade-off under progressively stricter regimes $\kappa 1 < \kappa 2 < \kappa 3$. Arrows: historical trajectory from high-granularity/high-coverage (circa 2015) to constrained operating points (circa 2024).

One structural response is a shift from individual-level to aggregate-level measurement. Aggregate methods operate on group expectations $E[Y|G] = f(E[X|G], E[Z|G]) + \varepsilon G$, where G denotes a cohort, treatment arm, or geographic region [4]. Information content is lower, but causal identification is often stronger because group-level randomization eliminates confounders without requiring individual tracking. Lift studies and geo-experiments provide unbiased causal estimates within the constraints of the granularity-coverage frontier [11]. Ivitskiy

[12] demonstrates that such approaches maintain validity as κ increases, precisely because they do not depend on restricted individual-level signal. This structural compatibility makes investment in aggregate infrastructure future-proof.

The implications for public administration are substantial. Tax compliance analytics, healthcare utilization measurement, and labor market tracking all face versions of the same constraint. The granularity-coverage inequality provides a formal framework for evaluating measurement architectures under current and anticipated regulatory regimes. A system designed for κ2 will fail when κ rises to κ3; planning for the trajectory of κ is therefore essential. When governments use digital platform data for urban planning, economic forecasting, or public health monitoring, the same reporting asymmetries documented in the commercial context introduce systematic distortions into the policy process. Ivitskiy [4] introduces the concept of “measurement sovereignty,” the maintenance of independent verification capabilities, as a governance priority applicable equally to commercial and public-sector contexts.

Three conclusions follow. First, measurement system design must begin with an explicit assessment of the prevailing κ and its likely trajectory, rather than assuming historical observability will persist. Second, aggregate methods that sacrifice individual precision for population-level validity represent the structurally sound response to increasing κ. Third, epistemic risk from reliance on intermediary-reported data demands independent verification mechanisms in both commercial measurement and public governance. Ivitskiy [4] further demonstrates that in recursive decision loops, where each cycle’s output parameterizes the next, the loss of measurement sensitivity compounds across stages: the effective variance grows as ω(t) falls, rendering progressively larger interventions statistically undetectable. Organizations that invest in aggregate measurement infrastructure now will find themselves better positioned as the constraint boundary continues to tighten; those that delay face a progressive loss of the ability to distinguish signal from noise in the systems they are tasked with monitoring.

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