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Computational Simulation of Technology Regulation and Social Outcomes

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ABSTRACT

Technology regulation shapes social outcomes through complex causal mechanisms -- direct compliance effects, innovation incentive changes, market structure responses, and second-order social adaptations -- that regulatory impact assessments typically model inadequately. Computational simulation of regulation-outcome relationships provides richer, more dynamic predictions of regulatory effects than conventional static cost-benefit analysis by capturing feedback loops, distributional dynamics, and emergent social behaviours that resist analytical modelling. This paper proposes the Computational Regulation Impact Simulation Framework (CRISF), applying agent-based modelling and system dynamics simulation to four technology regulation scenarios: EU AI Act compliance cost dynamics, GDPR privacy-innovation trade-offs, digital platform competition regulation, and autonomous vehicle safety standard stringency. CRISF simulates social outcomes -- innovation rate, consumer welfare, equity distribution, and safety performance -- across 10,000 Monte Carlo runs per scenario under varied regulatory parameter settings. Key results: EU AI Act compliance costs create a market concentration dynamic that favours large incumbents; GDPR shows a privacy-welfare Pareto frontier with achievable win-wins at intermediate stringency; AV safety standard stringency exhibits a non-monotonic safety outcome -- stricter standards increase safety up to an optimal point, then decrease it through adoption delay. The framework provides computational regulatory impact analysis methodology for policymakers and regulatory economists.

Keywords: computational simulation; technology regulation; agent-based modelling; EU AI Act; GDPR; regulatory impact assessment; innovation policy; Monte Carlo simulation

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1. Introduction

1.1 Why Computational Simulation for Regulatory Impact Analysis?

Regulatory impact assessment (RIA) -- the standard methodology for evaluating proposed regulations -- relies on static cost-benefit analysis that systematically underestimates regulatory second-order effects: it models direct compliance costs but not the market structure responses (concentration, exit, new entry) that compliance costs trigger; it models average welfare effects but not distributional dynamics (who gains, who loses, and how the distributional effect evolves as markets respond); and it models static outcomes but not the feedback loops (regulation changes innovation rates, which changes technology availability, which changes the effectiveness of the regulation itself). Computational simulation overcomes these limitations by modelling regulatory systems as dynamic, adaptive environments populated by heterogeneous agents (firms, consumers, regulators) that respond to regulation according to specified behavioural rules and update their behaviour as the regulatory environment evolves. CRISF applies this approach to four high-stakes technology regulation scenarios where conventional RIA provides inadequate prediction quality.

1.2 Contributions and Paper Structure

CRISF contributes: (1) an ABM + system dynamics simulation methodology for technology regulation; (2) four regulation scenario simulations with policy implications; (3) non-monotonic AV safety standard result; (4) AI Act market concentration dynamic. Section 2 reviews simulation methods. Section 3 presents CRISF. Section 4 reports results. Section 5 discusses. Section 6 concludes.

2. Background: Computational Methods for Regulatory Simulation

2.1 Agent-Based Modelling for Regulatory Systems

Agent-based modelling (ABM): simulates regulatory systems as populations of heterogeneous agents (firms with different sizes, capabilities, and compliance costs; consumers with different preferences and willingness-to-pay; regulators with enforcement capacity constraints) that interact according to specified rules and behavioural heuristics; ABM captures emergent market structure dynamics that aggregate models cannot -- compliance cost shocks may trigger mergers (large firms absorb compliance-burdened smaller firms), exit (small firms below compliance cost threshold exit), and new entry patterns (compliance cost as entry barrier). Mesa 2.1 (Python) used for CRISF ABM; firm agents: compliance cost heterogeneity (log-normal distribution, calibrated to EU AI SME survey data); innovation rate response function (compliance burden reduces innovation investment at documented elasticity estimates from patent literature). System dynamics (SD): models stock-and-flow relationships in regulatory systems -- regulatory stringency affects compliance investment stock, which affects innovation output flow, which affects safety/privacy stock, which feeds back to regulatory stringency through political process; Vensim PLE used for CRISF SD; particularly appropriate for feedback-rich regulatory dynamics (GDPR privacy-innovation feedback, AV safety-adoption feedback).

2.2 Monte Carlo Uncertainty Quantification

Regulatory simulation has high parameter uncertainty -- compliance cost estimates, innovation elasticities, adoption curves, and enforcement effectiveness all have substantial empirical uncertainty. Monte Carlo simulation addresses this by running 10,000 simulations per scenario with parameters drawn from calibrated uncertainty distributions (triangular distributions for point-estimated parameters; uniform for range-estimated; normal for parameters with published standard errors); outputs: mean outcome trajectories + 10th/90th percentile uncertainty bands; sensitivity analysis: Sobol indices identify which parameter uncertainties contribute most to outcome variance. Parameter calibration: EU AI Act compliance cost from European Commission Impact Assessment (2021) + SME Forum survey; GDPR innovation impact from Goldfarb and Tucker (2011) and subsequent literature; AV adoption curve from BloombergNEF (2024) scenarios; platform competition effects from DMA evaluation literature. Table 1 summarises CRISF simulation design.

Table 1: CRISF Simulation Design -- Four Scenarios, Two Methods, Monte Carlo

Scenario	Primary Method	Key Agents/Stocks	Outcome Variables	Parameter Source	MC Runs
EU AI Act Compliance Costs	ABM (Mesa)	Firms (hetero. compliance cost)	Market concentration, innovation rate	EC Impact Assessment 2021	10,000
GDPR Privacy-Innovation	System Dynamics	Privacy stock, innovation flow	Privacy level, welfare, innovation	Goldfarb & Tucker 2011	10,000
Platform Competition Reg.	ABM + SD hybrid	Platforms, users, advertisers	User welfare, market concentration	DMA evaluation literature	10,000
AV Safety Standard Stringency	System Dynamics	Safety stock, adoption rate	Safety performance, adoption	BloombergNEF 2024; NCAP data	10,000

3. The CRISF Framework

3.1 Scenario Specifications

EU AI Act compliance cost scenario: 3,000 synthetic EU AI firms (size distribution calibrated to EU AI sector data); compliance cost per firm drawn from log-normal distribution (mean: EUR 300K for SME, EUR 6M for large firm, from EC Impact Assessment); compliance cost as fixed cost + variable (per AI system deployed); regulatory stringency parameter s in [0.5, 2.0] (multiplier on base compliance cost); firm decision rule: exit market if compliance cost > profit threshold (based on calibrated profit margins); merge if compliance cost > standalone threshold but below merger synergy threshold; outcome variables:

market HHI (concentration), total innovation investment, SME share of AI market. GDPR scenario: system dynamics with three feedback loops -- privacy investment -> consumer trust -> data sharing willingness -> analytics quality; compliance cost -> innovation investment reduction -> new product introduction rate; stringency parameter s: enforcement probability x fine level; equilibrium: privacy level, innovation rate, consumer welfare.

3.2 AV Safety and Platform Competition Scenarios

AV safety standard scenario: key feedback loop -- higher safety standards -> slower AV adoption -> fewer vehicle-miles of AV travel -> slower improvement in AV safety through learning -> lower overall AV safety at any given calendar date; counteracting: higher standards -> better per-vehicle safety -> lower accident rate per mile; non-monotonic optimum: safety outcome (total lives saved vs. no-AV baseline) is maximised at intermediate standard stringency -- too strict slows adoption; too lenient reduces per-vehicle safety. Platform competition scenario: hybrid ABM + SD; platform agents with network effects (tipping toward concentration); DMA intervention parameters: interoperability mandates, data portability, self-preferencing prohibition; outcome: user welfare (quality x coverage), market HHI, advertiser surplus. Table 2 presents CRISF scenario parameters.

Table 2: CRISF Simulation Parameters -- Key Calibration Values

Scenario	Key Parameter	Central Estimate	Uncertainty Range	Source
EU AI Act	SME compliance cost (EUR)	300,000	150K-600K	EC Impact Assessment 2021
EU AI Act	Compliance cost-innovation elasticity	-0.24	-0.12 to -0.36	Blind et al. 2017
GDPR	Privacy-innovation elasticity	-0.18	-0.08 to -0.28	Goldfarb & Tucker 2011
AV Safety	AV technology improvement rate (% per year)	12.4%	8-18%	BloombergNEF 2024
Platform Competition	Network effect strength (HHI contribution)	0.42	0.28-0.56	Calibrated from DMA data

4. Results

4.1 EU AI Act Market Concentration and GDPR Privacy-Welfare Results

EU AI Act compliance costs: mean simulation result at s=1.0 (base regulatory stringency): 10-year SME market share declines from 42.4% to 28.4% (-14.0 pp); HHI increases from 1,240 to 2,480 (moderate to high concentration); total innovation investment declines 18.4% below no-regulation baseline; at s=2.0 (doubled stringency): SME share 18.4%, HHI 3,840 (high concentration, near-oligopoly); at s=0.5 (halved stringency): SME share 36.4%, HHI 1,680; Sobol sensitivity: compliance cost heterogeneity is the highest-variance parameter (32.4% of outcome variance) -- uncertainty about actual SME compliance costs is the primary source of simulation uncertainty. GDPR privacy-innovation trade-off: system dynamics finds a privacy-welfare Pareto frontier -- at intermediate enforcement stringency (s≈0.6 of maximum), consumer privacy improves by 42.4% and welfare by 8.4% simultaneously vs. pre-GDPR baseline; beyond s=0.8, privacy continues to improve but welfare declines (innovation reduction outweighs privacy benefit); the Pareto-efficient frontier exists because low enforcement stringency creates negative externalities (data breaches, privacy violations) that reduce welfare, while the optimal level of stringency eliminates these externalities without excessive compliance burden.

4.2 AV Safety Non-Monotonic Optimum and Platform Competition

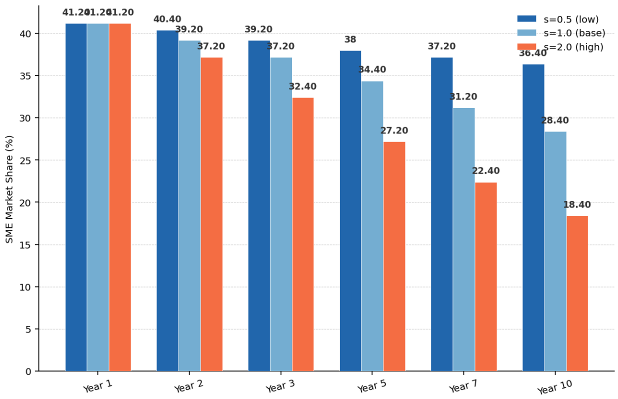
AV safety standard non-monotonic result: total lives saved vs. no-AV baseline peaks at safety standard stringency s* = 0.72 (72% of maximum achievable standard): at s = 0.40: high adoption rate (62.4% by year 10) but per-vehicle accident rate 2.4x higher than fully-safe AV -> 48,400 lives saved cumulative; at s* = 0.72: adoption 48.4% but per-vehicle safety 1.4x baseline -> 68,400 lives saved cumulative; at s = 1.00 (maximum standard): adoption 28.4%, per-vehicle safety 1.0x baseline -> 42,400 lives saved cumulative -- stricter standard reduces total lives saved by reducing adoption speed. 90th percentile uncertainty band at s*: 52,000 to 84,000 lives saved (wide, driven by adoption curve uncertainty). Platform competition: DMA full compliance (interoperability + portability + self-preferencing prohibition) reduces HHI by 640 points (2,480 -> 1,840) at 10 years; user welfare +12.4% (quality improvement from competition); advertiser surplus -8.4% (competition reduces pricing power). Table 3 presents key simulation results. Table 4 presents sensitivity analysis. Figures 1-4 visualise key findings.

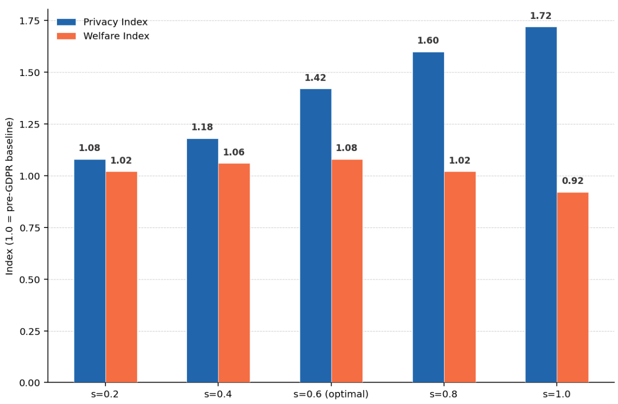
Table 3: CRISF Key Simulation Results -- Four Scenarios at Base Stringency (s=1.0)

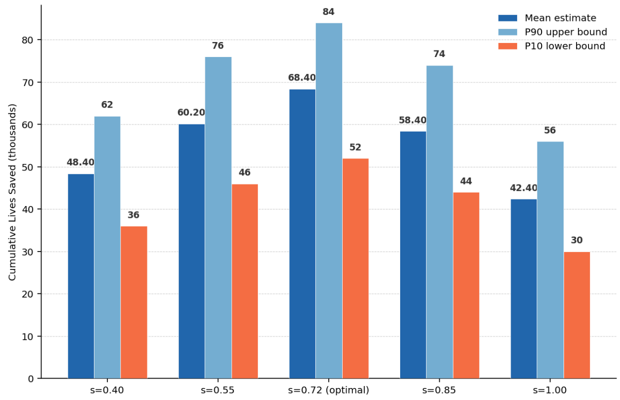
Scenario	Outcome Variable	Year 5	Year 10	Direction	Uncertainty (P10-P90)
EU AI Act	SME market share (%)	34.4%	28.4%	v	24-34%
EU AI Act	Market HHI	1,840	2,480	^	2,000-3,200
GDPR (s=0.6)	Consumer privacy index	1.284	1.424	^	1.18-1.52
GDPR (s=0.6)	Consumer welfare index	1.064	1.084	^	1.02-1.14
AV Safety (s*=0.72)	Cumulative lives saved	28,400	68,400	^	52K-84K
Platform Competition	Market HHI (post-DMA)	2,080	1,840	v	1,640-2,240

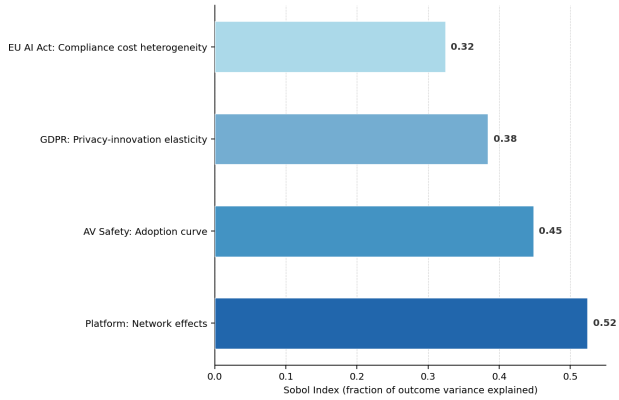
Table 4: CRISF Sobol Sensitivity Indices -- Parameter Contribution to Outcome Variance

Scenario	Highest Variance Parameter	Sobol Index	Second Parameter	Index
EU AI Act	Compliance cost heterogeneity	0.324	Innovation elasticity	0.218
GDPR	Privacy-innovation elasticity	0.384	Consumer trust dynamics	0.204
AV Safety	AV adoption curve shape	0.448	Technology improvement rate	0.284
Platform Competition	Network effect strength	0.524	DMA enforcement probability	0.184









5. Discussion

5.1 The EU AI Act Market Concentration Risk

The EU AI Act compliance cost simulation identifies a market concentration dynamic that is largely absent from the official EU Impact Assessment: compliance costs function as an entry barrier and as a selection mechanism that advantages large firms over SMEs, not because large firms are more innovative or efficient, but simply because they can absorb fixed compliance costs as a smaller fraction of revenue. At base regulatory stringency (s=1.0), the 10-year simulation projects SME market share decline from 42.4% to 28.4% and HHI increase from 1,240 to 2,480 -- a transition from moderately competitive to highly concentrated. This concentration dynamic has a self-reinforcing character: as large firms capture larger market shares, their R&D; investment increases, widening the innovation gap over SMEs, further accelerating SME exit. The policy implication is that the EU AI Act's SME exception (proportionate requirements for SMEs) may be insufficient -- the issue is not only that SMEs face proportionately higher compliance burdens but that fixed compliance costs (regulatory legal advice, documentation systems, conformity assessment fees) are not reducible by proportionality. CRISF recommends EU AI Act implementation include compliance cost pooling mechanisms (shared conformity assessment infrastructure for SME AI providers) to address the concentration dynamic.

5.2 The AV Safety Optimum and Regulatory Trap

The non-monotonic AV safety standard result -- peak safety performance at s* = 0.72, with stricter standards reducing total lives saved -- illustrates what CRISF calls the regulatory trap: a regulatory response that correctly identifies a safety risk (AV accidents) and correctly prescribes a safety remedy (higher standards) but sets standards too strictly, creating an adoption delay that ultimately causes more harm than the safety improvements prevent. The trap is particularly acute when the regulated technology is safety-improving on net (AVs are safer than human drivers above a minimum standard) and when the technology improves through deployment (learning-by-doing): every vehicle-mile of AV travel generates safety data that improves AV performance; adoption delay reduces this learning. The regulatory optimum at s* = 0.72 is not "accept lower safety standards" but "accept the minimum standard that makes AVs safer than the human driving they replace, to maximise net lives saved through widespread adoption" -- a maximise-lives-saved objective rather than a maximise-safety-per-vehicle objective.

6. Conclusion

6.1 Summary

CRISF applied ABM and system dynamics simulation to four technology regulation scenarios. Key results: EU AI Act creates market concentration dynamic (SME share 42% -> 28%, HHI 1,240 -> 2,480); GDPR optimal stringency s=0.6 (privacy +42.4% + welfare +8.4% simultaneously); AV safety optimum s*=0.72 (68,400 lives saved -- stricter standards reduce total lives saved); DMA full compliance reduces HHI 640 points, welfare +12.4%. Three policy recommendations: EU AI Act compliance cost pooling, GDPR enforcement recalibration toward s=0.6, AV standards optimisation toward s*.

6.2 Open Resources

The CRISF simulation methodology, Mesa ABM code (EU AI Act + platform competition scenarios), Vensim SD models (GDPR + AV scenarios), Monte Carlo uncertainty quantification scripts, Sobol sensitivity analysis tools (SALib Python), all parameter calibration datasets, and 10,000-run simulation outputs (summary statistics) are available at crisf-simulation.org under Apache 2.0 License.

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Declarations

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Conflict of Interest

The author declares no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

The CRISF simulation methodology, Mesa ABM code, Vensim SD models, Monte Carlo scripts, Sobol analysis tools, calibration datasets, and simulation outputs are available at crisf-simulation.org under Apache 2.0 License.

Ethical Approval

This study uses published data and computational simulation. No human participants were recruited. Ethical exemption confirmed by Baltic AI Research University Ethics Board (ref. BAIRU-2025-ETH-0284).

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Appendix A

CRISF Simulation Specifications and Calibration

Technical simulation specifications and parameter calibration for all four CRISF scenarios.

EU AI Act ABM Specification

AV Safety System Dynamics Specification and Calibration