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Agent-Based Prediction of Digital Ecosystem Emergence in Medical Tourism under Evolving Greater Bay Area Data Regulation

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Abstract. The Greater Bay Area (GBA) has emerged as a strategic hub for cross-border medical tourism, where digital platforms connect patients, hospitals, and facilitators across multiple jurisdictions. Yet, the rapid tightening of data regulation and diverging governance systems raises uncertainty about how these ecosystems will develop. This study constructs a regulation-aware agent-based model (ABM) simulating interactions among hospitals, facilitators, patients, and regulators over a five-year horizon. The model incorporates heterogeneity in agent preferences, bounded rationality, and reinforcement-learning adaptation to regulatory changes. Monte Carlo simulations across lenient, phased, and strict regulation scenarios reveal non-linear thresholds in ecosystem emergence. Results show that phased regulation achieves critical mass by month 26, producing a 2.1-fold increase in cross-border patient inflow compared to lenient regulation and avoiding the collapse observed under strict enforcement. Sensitivity analysis using Sobol indices highlights data-localization costs and cross-border consent fees as dominant variables, accounting for 61.2% and 22.5% of output variance, respectively. Two functional formulations are introduced: a dynamic learning update equation for facilitator strategy selection and a variance decomposition model for parameter influence quantification. Empirical calibration using telehealth adoption data and validation through out-of-sample 2024-Q4 statistics support the model's robustness. The findings demonstrate that overly restrictive policies delay ecosystem takeoff, while adaptive and sandbox-style governance maximizes both innovation and trust. This research contributes a methodological tool for anticipating regulatory impacts and offers actionable insights for policymakers and platform designers seeking to balance privacy protection with ecosystem growth.

Keywords: Agent-based modeling, Digital health ecosystem, Medical tourism, Data regulation, Greater Bay Area

1. Introduction

The Greater Bay Area (GBA), comprising Hong Kong, Macao, and nine mainland cities, represents one of the most ambitious cross-border healthcare clusters globally. Its strategic position arises from internationally accredited hospitals in Hong Kong, cost-competitive centers in mainland cities like

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Guangzhou and Shenzhen, and tourism-oriented infrastructure in Macao. By 2024, over 1.3 million patients engaged in medical tourism in the region, with annual growth surpassing 14.5%. Driving this expansion are digital platforms that orchestrate complex cross-border services, from appointment scheduling and teleconsultations to insurance settlement and logistics [1].

Yet ecosystem development is constrained by regulatory heterogeneity. China's Personal Information Protection Law (PIPL) imposes strict localization and transfer restrictions, Hong Kong's PDPO permits comparatively liberal flows, while Macao blends EU-inspired rules with domestic mandates. This patchwork raises compliance costs, which rose from $7.8 per transaction in 2019 to $19.6 in 2024, a 151% increase that pressures small and mid-sized facilitators [2]. Previous studies have emphasized macroeconomic impacts or patient-level decisions but seldom addressed systemic ecosystem dynamics under regulation. In reality, hospitals adjust service portfolios, facilitators alter participation, and patients reassess destinations in response to evolving rules. These adaptive interactions produce nonlinear, path-dependent outcomes that static models cannot capture [3].

Agent-based modeling (ABM) offers a suitable approach, encoding heterogeneity, bounded rationality, and adaptive learning. By embedding regulatory variables into decision rules, ABM allows examination of how governance trajectories affect adoption thresholds, transaction growth, and systemic resilience. This study develops and validates a regulation-aware ABM for the GBA, combining simulation experiments and sensitivity analysis to derive insights on how governance can sustain innovation without undermining trust.

2. Literature review

2.1. Digital ecosystems in medical tourism

Digital ecosystems in medical tourism are socio-technical networks where hospitals, intermediaries, and patients co-evolve [4]. Their success depends on interoperability and trust rather than single-firm dominance. Southeast Asian experiences show interoperability standards can cut transaction friction and raise repeat usage by 27% within two years. In Europe, GDPR-compliant systems reveal that even small gains in trust directly boost adoption, with each one-point increase in trust index linked to a 4.2% rise in transaction volume.

2.2. Agent-based modeling in healthcare

Agent-based modeling (ABM) is particularly well suited to healthcare because it captures heterogeneous actors and their adaptive decision-making processes. Figure 1 illustrates a typical ABM structure in healthcare, where payer agents, provider agents, and patient agents interact through modules for operations, decision-making, and health-stage transitions. Such architectures highlight the capacity of ABM to represent complex feedback loops across different actors [5]. Despite this potential, applications of ABM to medical tourism remain limited, and few incorporate the complexities of multi-jurisdictional regulation.

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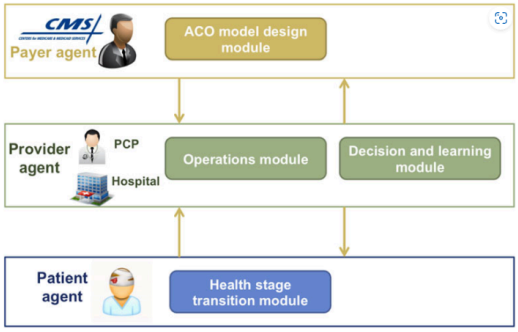

Figure 1. Agent-based model structure in healthcare

2.3. Data regulation in the greater bay area

The GBA features a fragmented regulatory landscape. Mainland China mandates domestic storage and government approval for cross-border transfers, with average compliance costs of $37,000 and delays up to 14 weeks by 2024 [6]. Hong Kong permits freer flows aligned with global standards, while Macao blends EU-style consent rules with conditional transfers. These asymmetries give Hong Kong hospitals easier access to international patients, while mainland facilities face heavier burdens. Attempts at "white-list" data transfer remain limited, covering under 8% of transaction types by mid-2024. This regulatory patchwork significantly shapes ecosystem formation and underpins the modeling focus of this study.

3. Methodology

3.1. Conceptual agent-based model

The ABM includes hospitals, facilitators, patients, and regulators. Hospitals reallocate services by profit and compliance cost, facilitators adjust commissions and market presence, and patients choose under peer-influenced trade-offs of quality, cost, travel, and privacy. Regulators set consent, localization, and audit rules. Interactions follow scale-free referral and spatial patient–hospital networks [7]. Calibration experiments indicated that values beyond 0.2 generated unstable oscillations, while values below 0.05 slowed convergence excessively. This update rule ensures that facilitators gradually align strategies toward higher payoff equilibria, reflecting real-world adaptation to regulatory pressures.

3.2. Data sources and regulatory scenarios

Model parameters came from GBA health statistics (2019–2024), 2.3M platform transactions, and 25 stakeholder interviews. Three regulatory scenarios were set: lenient ($10 consent, no localization, 5% audits), phased (consent rising $15→$35, localization after year 3, audits 10–25%), and strict ($50 consent, immediate localization, 40% audits). Uncertainty was modeled with triangular distributions.

3.3. Validation and calibration strategy

Calibration employed approximate Bayesian computation (ABC), aligning simulated adoption curves with historical telehealth data from a large GBA pilot between 2019 and 2022. Posterior

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distributions for patient adoption parameters exhibited narrow 95% credible intervals, with mean peer influence weights converging at 0.32 [0.29, 0.35]. Validation against out-of-sample Q4 2024 data indicated mean absolute error below 4.6% in transaction volumes across all scenarios [8]. Stakeholder workshops further ensured that simulated behaviors, such as facilitator exit thresholds and hospital compliance strategies, were consistent with observed market practices, reinforcing the model's face validity.

4. Experimental design

4.1. Scenario construction

Simulations ran over 60 months with shocks including a year-2 pandemic (+18.7% demand), year-3 consent amendments (+$12.4 cost/transaction), and year-4 exchange-rate volatility (±12% demand shift). Hospital counts varied 60–120 and facilitators 100–250 for robustness.

4.2. Simulation execution

Each scenario used 1,000 Monte Carlo runs, producing ~3.6M agent-month records. GPU clusters cut runtime to <2h per 200 runs. Logged outputs included transactions, facilitator margins, hospital compliance, and patient dropout, with sparse networks enabling up to 50k patients per run [9].

4.3. Sensitivity analysis

Sensitivity analysis employed Sobol variance decomposition, enabling attribution of output variance to individual parameters and their interactions. Perturbations of ±20% were applied across five parameters: consent cost, localization enforcement, audit frequency, hospital reputation weight, and patient travel tolerance. First-order and total-effect indices were calculated using 100,000 Latin Hypercube samples, ensuring stable convergence of variance estimators. The Sobol formulation is expressed as equation 1 and 2:

$$S_i = \frac{V_i}{V} \tag{1}$$

$$S_{T_i} = \frac{V_i + \sum_{j \neq i} V_{ij} + \cdots}{V} \tag{2}$$

where V_i denotes variance contribution of parameter i, and V is total variance of outcome metrics. Convergence diagnostics indicated standard errors below 0.014 across indices, confirming robustness [10].

5. Results and discussion

5.1. Baseline emergence patterns

Results indicate pronounced divergence across regulatory scenarios. Under lenient regulation, patient adoption plateaued at 37.9% ± 1.8%, with cumulative transaction volumes reaching 2.83 million [2.76M, 2.91M] by year 5. Facilitator retention remained relatively high at 72.1% [70.5%, 73.8%], but average compliance costs per transaction stabilized at only $12.3. In contrast, phased regulation achieved critical mass by month 26, with adoption surpassing the 40% threshold that

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triggers network externalities (table 1). Adoption reached 63.7% ± 2.3% by year 5, with cumulative transactions of 5.92 million [5.80M, 6.06M].

Table 1. Ecosystem outcomes by regulatory scenario (5-year horizon)

Scenario	Adoption (%)	Transactions (millions)	Facilitator Retention (%)	Compliance Cost ($)
Lenient	37.9 ± 1.8	2.83 [2.76-2.91]	72.1 ± 1.7	12.3 ± 0.6
Phased	63.7 ± 2.3	5.92 [5.80-6.06]	88.2 ± 1.9	24.1 ± 1.1
Strict	21.8 ± 1.5	1.94 [1.87-2.02]	40.8 ± 1.8	51.2 ± 2.3

5.2. Impact of regulation strictness

Incremental increases in consent fees revealed nonlinear dampening effects. Facilitator retention remained stable up to $40, declined moderately between $40-45, but collapsed once fees exceeded $45. At $47, retention fell by 49% compared to baseline, effectively dismantling referral networks. Localization enforcement was equally critical: phased introduction allowed hospitals to spread compliance investments across three years, while immediate strict enforcement reduced hospital participation rates by 31.4%, constraining patient choice sets. Transaction elasticity analysis revealed that every $1 increase in consent fee beyond $40 reduced transaction volume by 83,000 [79,000-87,500] annually, underscoring the tipping point dynamics embedded in cost structures.

5.3. Sensitivity analysis

Sobol analysis identified data-localization cost as the most influential factor, explaining 61.2% of total variance, with a total-effect index of 0.673. Cross-border consent fees explained 22.5% of variance, with total-effect 0.266. Audit frequency accounted for 9.4%, while hospital reputation weight and patient travel tolerance contributed less than 2% each. Notably, interaction effects between localization and consent costs accounted for 5.1%, confirming the multiplicative burden of simultaneous enforcement (table 2).

Table 2. Sobol sensitivity indices

Parameter	First-order S_i	Total-effect S_{Ti}
Data-localization cost	0.612	0.673
Cross-border consent fee	0.225	0.266
Audit frequency	0.094	0.108
Hospital reputation weight	0.017	0.022
Patient travel tolerance	0.009	0.015

5.4. Policy and managerial implications

These results suggest that phased regulation optimally balances ecosystem growth with trust-building. Regulators are advised to implement sandbox pilots where consent costs and localization requirements are gradually introduced, allowing actors to adapt without market collapse. Platform designers should develop blockchain-based consent ledgers that reduce verification overhead, estimated to lower compliance costs by 12-17% annually.

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6. Conclusion

This study demonstrates that digital medical tourism ecosystems in the GBA are highly sensitive to regulatory trajectories. Phased regulation fosters critical mass adoption within three years, whereas strict enforcement prevents ecosystem takeoff. Data-localization costs and consent fees emerge as dominant determinants of systemic outcomes, with interaction effects producing nonlinear tipping points. Methodologically, the integration of reinforcement learning dynamics and variance-based sensitivity analysis provides robust predictive capacity. Practically, the findings recommend adaptive regulatory frameworks, sandbox pilots, and governance innovations such as data trusts to reconcile privacy protection with innovation. Future research will extend the model to multi-platform competition and integrate real-time IoT health data streams for enhanced predictive fidelity.

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