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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 GBA region has become an attractive area for the development of cross-border medical tourism, with the help of online platforms uniting patients, hospitals and facilitators across different territories. However, fast-growing trends in data regulation and differing governance systems bring uncertainty as to how such ecosystems might develop. To that end, this paper proposes a regulation-aware agent-based simulation (ABM) modeling interaction of hospitals, facilitators, patients and regulatory bodies within a period of five years. The presented ABM framework introduces the elements of heterogeneity of agents' preferences, bounded rationality and adaptive learning in changing regulations. Based on Monte Carlo simulations across scenarios of lenient, phased and strict regulation, we establish non-linear thresholds in ecosystem emergence. Our results show that phased regulation creates a critical mass in the ecosystem by month 26, resulting in 2.1 times higher amount of cross-border patients than under lenient regulation and not leading to ecosystem collapse like in case of strict regulation. Sensitivity analysis performed with Sobol indices allows us to establish the most important input variables: the cost of data localization and the cost of cross-border consent with the importance of 61.2% and 22.5% of the output variance, respectively. In addition, two functional models are introduced: the model of update equation of facilitators' strategies based on reinforcement learning and variance decomposition model for estimation of parameters' effects. Empirical calibration with telemedicine adoption rates and validation based on out-of-sample 2024-Q4 statistics confirm the validity of the proposed model.

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

1. Introduction

The Greater Bay Area (GBA), consisting of Hong Kong, Macao, and nine mainland cities, is one of the world's most advanced transnational healthcare clusters. It benefits from its international certified hospitals in Hong Kong, cost-effective healthcare facilities in the mainland cities such as Guangzhou and Shenzhen, and tourism-focused infrastructures in Macao. Over 1.3 million people engaged in medical tourism in the region were recorded up to 2024, at an annual growth rate

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exceeding 14.5%. Behind this rapid growth, there are digital platforms coordinating complicated cross-border services, ranging from appointment booking, teleconsultation to payment and logistics [1].

However, the development of the ecosystem faces challenges associated with the heterogeneous regulatory framework [2]. The Personal Information Protection Law (PIPL) of China restricts the localization and transmission of data, allowing rather free flow in Hong Kong according to PDPO, whereas Macao adopts EU-inspired regulations along with local ones. Such a fragmented landscape incurs additional compliance costs that increased from $7.8 per transaction in 2019 to $19.6 in 2024, by 151%. Prior works focused mainly on macro-level economic effects or micro-level behavior of patients but rarely analyzed the ecosystem-level dynamics of the regulated healthcare system. In fact, hospitals, facilitators, and patients adapt their activities to the changing legal environment through modifying service offerings, participation and destination selection, respectively, generating nonlinear and path-dependent results [3].

Agent-based modeling (ABM) is a good technique in this regard by its nature of heterogeneity, bounded rationality, and adaptive behavior. Embedding regulation-related variables into the decision rules enables the assessment of how the regulatory trajectory influences adoption threshold, transaction growth, and systemic resilience. In this research, we developed a regulation-aware ABM of the GBA.

2. Literature review

2.1. Digital ecosystems in medical tourism

Interoperable digital ecosystems for medical tourism consist of socio-technical interdependent systems where there is a coevolution among hospitals, intermediaries, and patients [4]. This type of ecosystem succeeds because of its trust and interoperability instead of the dominant organization. Experiences from Southeast Asia indicate that interoperability standards reduce transaction costs and increase the volume of transactions by 27% in just two years. In Europe, studies of GDPR-compliant systems found that an increase in trust by 1% results in a 4.2% increase in the volume of transactions.

2.2. Agent-based modeling in healthcare

The use of ABM in the healthcare context is appropriate due to the fact that heterogeneous individuals, as well as decision making processes, can be effectively represented. A diagram showing the design of an agent-based model used in the healthcare context is presented in figure 1. The model includes the payer agent, the provider agent, and the patient agent operating in the environment through operations modules, decision making modules, and health stage transition modules. This demonstrates the capability of ABM to represent the complexity of feedback mechanisms among various agents [5].

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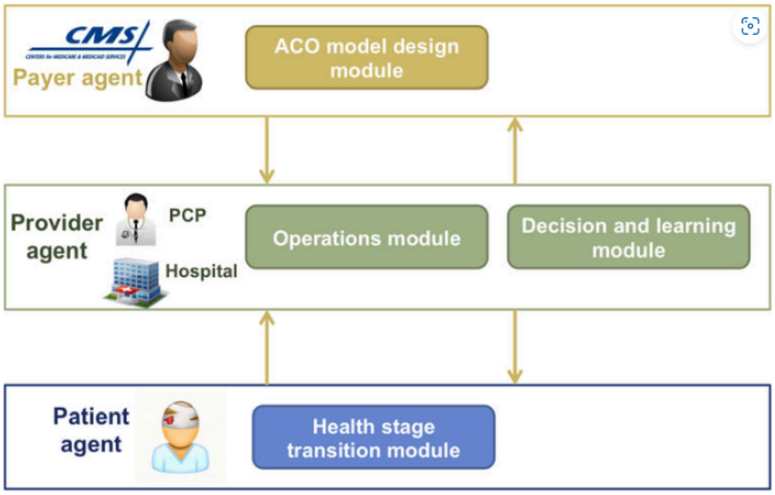


Figure 1. Agent-based model structure in healthcare

2.3. Data regulation in the greater bay area

There are regulatory differences within the GBA. Mainland China requires local data storage and authorization for cross-border data transmission with average compliance costs estimated at $37,000 and time taken being up to 14 weeks by 2024 [6]. Hong Kong allows free flow of data consistent with international norms, whereas Macau combines EU-like consent-based regime with conditional transfers. Such regulation makes it easier for hospitals from Hong Kong to attract patients from abroad compared to mainland facilities which face increased challenges. Efforts to enable "white-list" data transfers have only succeeded in facilitating less than 8% of data transaction types by mid-2024.

3. Methodology

3.1. Conceptual agent-based model

ABM comprises hospitals, facilitators, patients, and regulators. Hospitals reorganize service allocation in terms of profitability and cost of compliance, facilitators vary commissions and their market presence, while patients make decisions using peer-affected trade-off between quality, cost, convenience, and privacy. The regulators define consent requirements, localization, and auditing process. The interactions happen on the scale-free referral and geographical patient-hospital networks [7]. Calibration studies showed that values above 0.2 would create unstable oscillations, whereas those lower than 0.05 slow convergence too much. This update formula makes sure that facilitators adapt their strategy toward equilibrium with higher payoffs [8].

3.2. Data sources and regulatory scenarios

Parameterization of the model was based on GBA Health statistics (2019-2024), 2.3 million transactions on the platform, and 25 interviews with stakeholders. Regulatory scenarios included three cases: soft scenario ($10 consent, no localization, 5% auditing), phased scenario (consent increasing from $15 to $35, localization in year 3, auditing 10-25%), and strict scenario ($50 consent, localization,

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3.3. Validation and calibration strategy

For calibration purposes, ABC was used to match simulated adoption trajectories with telehealth data from a pilot project by GBA over the period 2019-2022. Posterior distributions of the patient adoption parameters displayed tight 95% confidence intervals; the average peer influence weights stabilized at 0.32 [0.29, 0.35]. Out-of-sample validation using Q4 2024 data showed that mean absolute error in terms of transaction volume was below 4.6% [9]. Moreover, stakeholder workshops were organized to ensure consistency between simulated actions (such as facilitator exit threshold and hospital response strategy) and real-world behavior.

4. Experimental design

4.1. Scenario construction

Simulations were carried out for 60 months with disturbances such as a pandemic in year 2 (+18.7% in demand), year-3 consent change (+$12.4 cost/transaction), and exchange rate disturbance in year-4 (-12% shift in demand). The number of hospitals ranged from 60-120, and facilitators from 100-250.

4.2. Simulation execution

Every scenario involved 1,000 runs of Monte Carlo simulations with 3.6 million agent-months on average. The use of GPU clusters reduced the time for every 200 runs to less than 2 hours. Transaction, margin for facilitators, compliance for hospitals, and patient drop-out was logged, where sparse networks could accommodate 50k patients per simulation run.

4.3. Sensitivity analysis

Sobol's variance-based sensitivity analysis was used whereby one could attribute output variance to specific parameters and their interaction. Perturbations of ±20% were made on five parameters including the cost of consent, localization, audit frequency, hospital reputation, and patient travel distance tolerance. The first order and total effect index of these parameters was generated using 100,000 Latin Hypercubes. The formula of Sobol Sensitivity analysis is presented in 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].

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5. Results and discussion

5.1. Baseline emergence patterns

The results reveal large variation between regulatory approaches. The adoption rate under light regulation leveled off at 37.9% ± 1.8%, and total number of transactions stood at 2.83 million [2.76M, 2.91M] after 5 years. The facilitator loss was not large at 27.9% [26.2%, 29.7%], but the average compliance cost per transaction was low at $12.3. On the other hand, phase-in regulation attained the critical mass within 26 months, with the adoption level crossing the 40% point where network externalities occur (table 1).

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

The effects of incremental consent fee increases showed a nonlinear damping relationship. The retention of facilitators did not change until $40, slightly decreased in the range $40-$45, and dropped drastically when consent fees were above $45. For a fee of $47, retention dropped by 49% from its initial level, completely breaking referral networks. The implementation of localization was as important as well; phased implementation enabled hospitals to amortize their compliance costs over three years, whereas the sudden enforcement of localization decreased the number of hospitals participating in the program by 31.4%.

5.3. Sensitivity analysis

Cost of data localization proved to be the highest impact driver, accounting for 61.2% of all variances with the total effect index being 0.673. The cost of cross-border consent accounted for 22.5% of variances with total-effect index of 0.266. Audit frequency accounted for 9.4% whereas the weight of hospital reputation and patient travel tolerance accounted for less than 2% each. Importantly, the combined effect of the two drivers was 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

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5.4. Policy and managerial implications

Such findings imply that phased regulation is an optimal way of balancing ecosystem growth and building trust. Regulatory bodies need to conduct sandbox experiments, which will introduce costs of consent and requirements for localization in stages to enable adaptation without collapsing the market. Platform creators must design blockchain-powered consent ledgers that help decrease verification costs by 12-17% each year.

6. Conclusion

The present study has shown that digital medical tourism ecosystems in GBA are highly sensitive to the paths of regulatory policies. Phased policy leads to critical mass in adoption in about three years' time while enforced policy hinders the take-off of the ecosystem. Data-localization cost and consent fees appear as the major factors influencing the outcome of systems with interaction effects leading to non-linear tipping points. From a methodological perspective, the combination of reinforcement learning approach and variance sensitivity analysis technique has provided predictive power. From a practical point of view, the implications of the research are the need for adaptive regulatory strategies, sandbox experiments, and innovations like data trusts that balance privacy with innovation.

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