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AGENT-BASED MODEL OF DYNAMICS BETWEEN OBJECTIVE AND PERCEIVED QUALITY OF HEALTHCARE SYSTEM

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ABSTRACT

Nationwide patient concentration poses a significant burden on healthcare systems, driven primarily by patients' perception that metropolitan regions offer superior care quality. To better understand this phenomenon, we present an agent-based model to examine how objective quality (OQ) and perceived quality (PQ) co-evolve in a free-choice healthcare system, using South Korea as a salient case. Four interaction mechanisms (Preferential Hospital Choice, Scale Effect, Quality Recognition, and Word-of-Mouth) configure a feedback loop between OQ and PQ: as concentration of choice elevates a hospital's OQ through scale effects, utilization in turn updates and disseminates PQ. We identify three emergent phenomena—Local Dominance, Global Dominance, and Asymmetric Quality Recognition—and interpret how each contributes to patient outmigration. Building on these insights, we further explore strategies such as "local tiering" and "information provision." We envision this model-based approach will deepen understanding of OQ–PQ dynamics, offering insights to address nationwide healthcare utilization issues in various contexts.

1 INTRODUCTION

The modern healthcare system empowers patients to choose hospitals not only based on medical needs but also on personal preferences or supplier-related factors (Victoor et al. 2012). While this flexibility enhances individual choice, it also creates imbalances in hospital and utilization at both the individual and system levels. When patient preferences are concentrated on a limited number of providers, healthcare systems become vulnerable to significant system-level inefficiencies (Fulton 2017). These inefficiencies manifest themselves as *hospital bypass behavior* at the individual level and *utilization concentration* at the systemic level, both of which contribute to regional disparities in access and quality of healthcare (Varkevisser and van der Geest 2007).

Such disparities place a significant burden on both individuals and the broader healthcare system. For patients, geographical disparities in access and quality mean longer travel times and higher costs to access high-quality care (Massarweh et al. 2014). Hospitals overwhelmed by large patient volumes become saturated and fatigued, resulting in diminished quality and efficiency of care, such as the increased risk of medical errors, reduced consultation times, and longer waiting periods (Kang 2014; Moscelli et al. 2023). Meanwhile, underutilized hospitals struggle financially, often leading to reduced resources, facility degradation, and staff attrition.

While hospital bypassing and utilization concentration is a global phenomenon, it is particularly pronounced and clearly delineated in South Korea through a pattern known as *outmigration*. Outmigration refers to a specific form of hospital bypassing behavior in which patients living outside of Seoul, the capital of South Korea, bypass local facilities to seek care at a small number of tertiary hospitals located in Seoul (Lee et al. 2025). The disproportionate concentration of patients in Seoul's top tertiary hospitals – often called the "Big 5" – leads to a stark polarization in cancer care between the capital and other regions. This dynamic accelerates the decline of healthcare services in underserved areas, compounding challenges for hospitals in those regions and gradually undermining their quality (Kim 2020). The extensive transportation infrastructure in South Korea enables same-day round trips to Seoul from nearly any region, further reinforcing this pattern.

We argue that the primary motivation behind the outmigration lies in patients' perception that metropolitan hospitals offer higher quality care than local hospitals (Lee et al. 2025; Lee 2025). In other words, patients perceive the quality of individual metropolitan hospitals to be higher than that of nearby alternatives. In addition, a broader regional preference also influences this decision. Patients tend to favor receiving care in metropolitan areas, perceiving the overall standard of care in these regions to be superior to that of their local communities. Preliminary qualitative studies, including group model building conducted by the authors, have identified that patients have a distinct sentiment of trust towards the region in which they reside, apart from their perceptions of individual hospitals (Lee 2025). Therefore, we posit that outmigration is driven by two related factors: the higher perceived quality of specific metropolitan hospitals, which we refer to as *Perceived Hospital Quality* (PHQ), and the general perception that metropolitan regions, as a whole, offer better healthcare, which we denote as *Perceived Regional Quality* (PRQ).

Then, there is an interplay between the perceived quality and true, actual quality of a hospital. In this work, we refer to the latter as *Objective Hospital Quality* (OHQ). Because PHQ is inherently subjective, it does not always align with objective measures of hospital performance (Jaworeck 2024; Naik 2022; García-Lacalle and Bachiller 2011). This misalignment between OHQ and PHQ stems from information asymmetry in healthcare, limited public access to reliable quality information, and the influence of word-of-mouth (Jiang et al. 2024; Brown et al. 2023; Pauli et al. 2023). Additionally, there is a time lag between the perceived quality and objective quality; when the objective quality of a hospital changes, it does not immediately translate into perceived quality. Inherent resistance to changing beliefs means that recognition of objective quality requires sufficient exposure to shift patients' perception through actual utilization or influence from others, creating time lags between PHQ and OHQ.

Our research aims to simulate the dynamics among these three quality constructs – PHQ, PRQ, and OHQ. We propose these quality constructs dynamically interact and co-evolve through several underlying mechanisms. Specifically, we implemented four key mechanisms to reflect the complex interplay among these quality metrics: *Hospital Choice, Scale Effect, Quality Recognition*, and *Word-of-Mouth*. Patients' PHQ and PRQ drive their choice and utilization of a particular hospital in a particular region (*Hospital Choice*) (Varkevisser et al. 2012). These choices elevate OHQ of those hospitals chosen by a large number of patients (*Scale Effect*) (Luft et al. 1987; Chhatre et al. 2024). In the opposite direction, OHQ influences PQ as patients experience a hospital's care quality through utilization and incorporate this experience into their perceptions (*Quality Recognition*). In addition to such direct experiences, the updated perceptions propagate throughout the population by sharing their experiences (*Word-of-Mouth*) (Arndt 1967). Detailed structures and implementations of each mechanism are described in 2.2.

Building on these quality dynamics, we develop an agent-based model to examine the co-evolution of objective and perceived quality factors within a free-choice healthcare system, using South Korea as a salient case. The primary objective of this study is to investigate how complex and dynamic interactions among these factors produce joint effects and emergent system-level phenomena. By doing so, we deepen our understanding of the dynamics among quality metrics and interpret how their interactions underpin the hospital utilization concentration phenomenon. Additionally, we test whether narrowing the gap between objective and perceived quality can reduce patient outmigration by implementing an *Information Provision Policy* (IPP). The IPP provides individuals with direct information about hospitals' OHQ, replacing their PQ measures. We compare two IPP alternatives (Hospital-level IPP versus Regional-level IPP) to identify conditions under which each policy effectively mitigates patient concentration.

The remainder of this paper is structured as follows. Section 2 presents the simulation model and discusses parameter configuration and experimental design. Section 3 explores the emergent phenomena of quality dynamics, illustrates how parameter variations impact outmigration, and evaluates the Information Provision Policy. We also include a comprehensive sensitivity analysis to demonstrate how parameter changes affect policy outcomes. Finally, Section 4 summarizes the study's contributions, acknowledges limitations, and proposes directions for future research.

2 METHODS

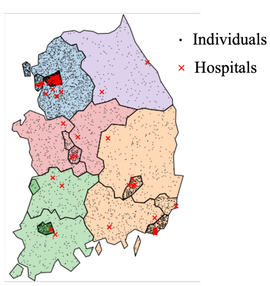
2.1 Simulation Configuration

Our agent-based simulation models the dynamics between individuals, who make preferential choices based on their own perceived quality, and hospitals, whose objective quality evolves according to patient inflows. We implemented our simulation with a focus on South Korean cancer patients. Cancer is a leading contributor to patient concentration problems in South Korea: its high clinical severity combined with relatively low urgency amplifies the role of patients' choice in seeking treatment.

2.1.1 Agents Setting

Individuals are geographically distributed across South Korea's 17 administrative districts, aggregated into five major regions: SM (Seoul Metropolitan), YN (Yeongnam), HN (Honam), CC (Chungcheong), and GW (Gangwon). We simulate a total population of 5,126, corresponding to 0.01% of the population distribution across the 17 districts. Each individual's coordinate is randomly assigned within their respective district. All individuals begin as susceptible to cancer, and at each time step, a predetermined number of individuals (n_p, 28 in our baseline setting) are randomly designated and diagnosed as cancer. Once diagnosed, these individuals choose and utilize a hospital for treatment based on their current choice probabilities.

Hospitals in the simulation consist of all 47 tertiary hospitals in South Korea, excluding secondary or lower-level hospitals, reflecting our specific focus on cancer care. Actual geographic coordinates are used to locate these hospitals, as shown in Figure 1. Figure 1 illustrates the detailed configuration used for agent initialization and provides a geographic visualization of the distribution of hospitals and individuals.



Region	Population	Number of Hospitals
SM (Seoul Metropolitan)	2,603	23
YN (Yeongnam)	1,255	13
HN (Honam)	564	5
CC (Chungcheong)	555	4
GW (Gangwon)	152	2

Figure 1: Agents (Individuals and hospitals) visualized on the map of South Korea

2.1.2 Quality Constructs

Each hospital possesses a single Objective Hospital Quality (OHQ) value, while each individual holds their own perceived quality (PQ) values for all 47 hospitals (PHQ) and the 5 defined regions (PRQ), respectively. All quality measures range from 0 to 5, with their initial values set between 2 and 3. This narrow initial range allows the simulation to generate intensified divergence in quality measures and intensified patient concentration phenomena. Details regarding the initial settings for each quality construct used in the simulation can be found in Section 2.3.1.

2.2 Quality Interaction Mechanisms

The simulation incorporates four key mechanisms that dynamically drive the interactions between OQ and PQ. Patients choose hospitals based on their perceptions on their service quality and geographical context including distance to hospitals (*Preferential Hospital Choice*). Increased patient inflows to certain hospitals lead to improvements in the OHQ of those hospitals through volume-outcome relationships and other indirect benefits associated with a higher patient volume (*Scale Effect*). Patients update their perceived quality values upon utilizing a hospital and recognizing its care quality (*Quality Recognition*). Lastly, these updated perceptions are disseminated through social interactions, amplifying or moderating perceptions towards regions and hospitals (*Word-of-Mouth*). These mechanisms are combined into a single system and interact within a complex feedback loop, as illustrated in Figure 2. Details of such dynamics are elaborated below.

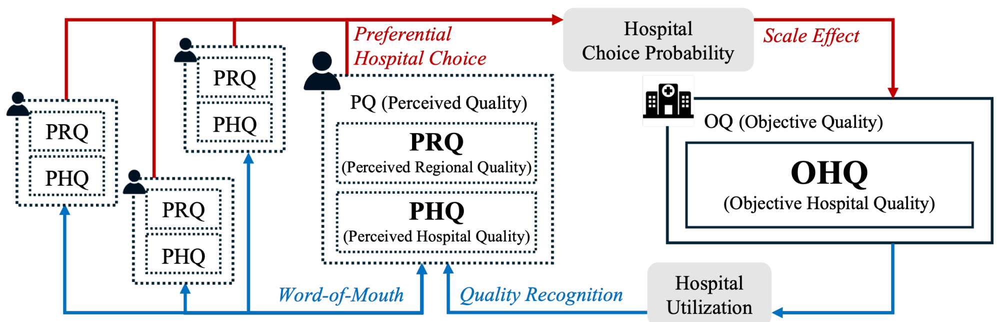


Figure 2: Quality interplay mechanisms and feedback loop

2.2.1 Preferential Hospital Choice

At each time step, every individual calculates choice probabilities for each hospital based on their perceived quality (PQ) and travel cost (Gooding 2000). Among these individuals, those who are designated as cancer patients at each time step, select and utilize a hospital according to their respective choice probabilities. We employed a *two-step hierarchical logit model* (Drakopoulos 1994) to characterize the hospital choice mechanism, in which decision-makers first choose among groups of alternatives (in our simulation, regions) and subsequently make secondary choices within the chosen group (hospitals within each region).

In the first stage of regional choice, each individual chooses among the five regions. The observed utility for individual i selecting region $r \in R = \{SM, YN, HN, CC, GW\}$ is given by:

$$V_{i,r} = \beta_{\text{PRQ}} \times \text{PRQ}_{i,r} + \beta_d \times e^{-\delta d_{i,r}} \tag{1}$$

where $\text{PRQ}_{i,r}$ represents individual i's perceived regional quality of region r, and $\text{d}_{i,r}$ denotes the distance from the individual's location to representative coordinates of region r. Each region's representative coordinate is set at a major train station for each region (e.g., Seoul Station for SM, Busan Station for YN). Distances are incorporated into the model as a travel cost term, $e^{-\delta d_{i,r}}$, with distance decay parameter δ. The parameters β_{PRQ} and β_{d} control how strongly perceived quality and distance influence the utility. Following the logit model's formulation, the regional choice probability is calculated as follows:

$$P_i(r) = \frac{e^{V_{i,r}}}{\sum_{r' \in R} e^{V_{i,r'}}} \tag{2}$$

In the second, hospital-level choice stage, the individual selects among the hospitals within the chosen region. Here, we use a scale-adjusted multinomial logit model to introduce varying degrees of choice randomness. The observed utility for individual i selecting hospital j within region r is given by:

$$V_{i,h} = \beta_{\text{PHQ}} \times \text{PHQ}_{i,h} + \beta_d \times e^{-\delta d_{i,h}} \tag{3}$$

where $\text{PHQ}_{i,h}$ and $\text{d}_{i,h}$ represent individual i's PHQ and distance for hospital h, respectively.

The probability of choosing hospital h given region r_h(in which hospital h is located) is:

$$P_i(h|r_h) = \frac{e^{\pi \times V_{i,h}}}{\sum_{h' \in r_h} e^{\pi \times V_{i,h'}}} \tag{4}$$

For the hospital-level choice within the chosen region, we incorporate the scale parameter π to reflect the rationality of patients in their hospital choices. Smaller values of π indicate a higher degree of randomness in hospital selection within a region (e.g., if $\pi = 0$, then $P_i(h) = 1/|H_r|$), while larger values of π imply that patients are more sensitive to differences in utility (e.g., $\pi = \infty$, patients always choose the hospital with the highest $V_{i,h}$). This allows the model to reflect behavior under which patients, after choosing a region, do not strongly discriminate among hospitals within that region.

The overall probability of selecting hospital h thus combines the probabilities from both regional and hospital-level choices:

$$P_i(h) = P_i(r_h) \times P_i(h|r_h) \tag{5}$$

2.2.2 Scale Effect

Scale Effect refers to the mechanism through which a hospital's OHQ changes based on its relative patient inflow. Hospitals attracting higher-than-average patient volumes benefit from increased opportunities for practice (the so-called "practice makes perfect" effect), and may also gain financial advantages due to economy of scale, that enable further investment in staff, facilities, and equipment. Conversely, hospitals with lower-than-average patient inflows encounter stagnation or reductions in their OHQ.

We implement this effect with the following update rule for each hospital h at time $t+1$:

$$\text{OHQ}_h^{t+1} = \text{OHQ}_h^t \times \left(1 + \mu_{\text{scale}}\left(\overline{P}(h) - \tfrac{1}{|H|}\right) \times \left(1 - \left|\tfrac{\text{OHQ}_h^t - 2.5}{2.5}\right|\right)\right) \tag{6}$$

where OHQ_h^{t+1} is the hospital's OHQ in the next timestep, and OHQ_h^t is the current OHQ. The parameter μ_{scale} controls the magnitude of the scale effect. The term $\overline{P}(h)$ denotes the population-averaged choice probability directed toward hospital h, while $|H| = 47$ is the total number of hospitals. Thus, $\overline{P}(h) - (1/|H|)$ indicates the surplus choice probability of hospital h compared to the equal-share fraction $(1/|H|)$. A positive value raises OHQ, whereas a negative value lowers it.

The additional factor $(1 - |(\text{OHQ}_h^t - 2.5)/2.5|)$ measures how close the current OHQ is to the upper (5) or lower (0) boundary. Given that this factor diminishes near 0 or 5, scale effects weaken as OHQ approaches either of the two boundaries, limiting further upward or downward movement.

2.2.3 Quality Recognition

Quality Recognition refers to the mechanism through which patients update their perceived quality based on direct hospital utilization. Those individuals who are newly diagnosed with cancer choose a hospital and, by using it, directly experience its OHQ. As a result, it leads to updates in both their PHQ for that particular hospital, as well as the PRQ for the region to which the hospital belongs. Formally, when patient i visits hospital h located in region r_h, their PHQ and PRQ are updated as follows:

$$\text{PHQ}_{i,h}^{t+1} = \mathbb{1}_{i,h}^t \times \mu_{recog}(\text{OHQ}_h^t - \text{PHQ}_{i,h}^t) + \varepsilon_{i,h}^t \tag{7}$$

$$\text{PRQ}_{i,r_h}^{t+1} = \mathbb{1}_{i,h}^t \times \mu_{recog}(\text{OHQ}_h^t - \text{PRQ}_{i,r_h}^t) + \varepsilon_{i,r_h}^t \tag{8}$$

where OHQ_h^t is the objective quality of hospital h at time t, $\text{PHQ}_{i,h}^t$ and PRQ_{i,r_h}^t are patient i's current perceived hospital and regional quality, respectively, and $\varepsilon_{i,h}^t$ and ε_{i,r_h}^t represent gaussian-distributed random noise with standard deviation of σ_{recog}. $\mathbb{1}_{i,h}^t$ is an indicator function, taking the value 1 if patient i visits hospital h at timestep t, and 0 otherwise. The parameter μ_{recog} determines the magnitude of quality recognition.

2.2.4 Word-of-Mouth

Word-of-Mouth (WOM) mechanisms disseminate changes in perceived quality (PQ) throughout the patient population, channeling individual updates caused by quality recognition or other factors into broader social feedback through explicit and implicit networks. In this study, we conceptualize WOM as originating from two forms of interaction (Martin 2017; Fan et al. 2021).

Direct interaction refers to the transmission of information and perceptions primarily through close, kin-based networks (e.g., family and friends) (De Cruppé, W and Geraedts, M 2011; Martin 2017; Fan et al. 2021). In this study, patients who are geographically close to one another are assumed to be socially connected, share their experiences, and update quality perceptions, leading to local convergence in perceptions. Cancer patients, who already have their own first-hand utilization of a hospital, exert a stronger influence due to the perceived credibility of their experiences.

Indirect interaction, by contrast, involves broader assimilation of regional sentiment through media sources, online reviews, or intangible social ambiences (Li et al. 2015; Huppertz et al. 2020). In this indirect channel, each patient's PQ gradually converges toward the average of their residing region, shaping hospital and regional reputations system-wide. Detailed rules and implementations of WOM mechanisms can be found in Appendix A.

2.3 Simulation

2.3.1 Baseline Parameters

To explore the qualitative dynamics and emergent phenomena, we established a baseline parameter set to execute the simulation. Specifically, the *initial parameters* (initial PRQ values, coefficients and parameters in hospital choice model β_{PRQ}, β_{d}, δ, which determine the regional outmigration pattern at the first time step, were calibrated to replicate the real-world empirical data of South Korea—reflecting the current trend of patient concentration in the Seoul Metropolitan region. Other quality constructs (PHQs and OHQs) are each initialized to the same value as the PRQ of the region in which the hospital belong to (r_h), plus Gaussian-distributed random noise. Other parameters were assigned appropriate initial values and are later subjected to analyze the impact of their variations. Details of baseline parameters can be found in Appendix B, and the process of calibrating initial parameters to empirical dataset is described in Appendix C.

2.3.2 Simulation Procedures

The simulation proceeds through the following iterative steps:

1. Set the quality constructs (PRQ, PHQ, OHQ) according to the calibrated values of baseline PRQ.
2. At each timestep t:
   (a) Each patient i calculate their hospital choice probabilities ($P_i(h)$) following Eq.(1)–(5), based on their current perceived qualities (PHQ, PRQ) and distance to hospitals.
   (b) A predefined number of agents (n_p) are diagnosed with cancer, and select the hospital according to their preferential choice probabilities.
   (c) Cancer patients utilize their chosen hospital, and update their PQ via the *quality recognition* mechanism: Eq.(7)–(8).
   (d) Each hospital's OHQ are updated based on the *scale effect* mechanism described in Eq.(6), using the population-averaged preferential hospital choice probabilities calculated for each hospital.
   (e) Each individual's PQ are updated based on *word-of-mouth* mechanisms.
3. Repeat Step 2 until the designated number of simulation cycles (500 timesteps) is completed.

3 RESULTS AND DISCUSSION

3.1 Emergent Phenomena

In this section, we examine the simulation results under the baseline setting, and discuss the *emergent phenomena* that arise from the feedback loop among objective quality (OHQ), and perceived quality (PHQ and PRQ). Figure 3 shows how quality constructs evolve over time under the baseline setting. We characterize three emergent phenomena: *Local Dominance*, *Global Dominance*, and *Asymmetric Quality Recognition*.

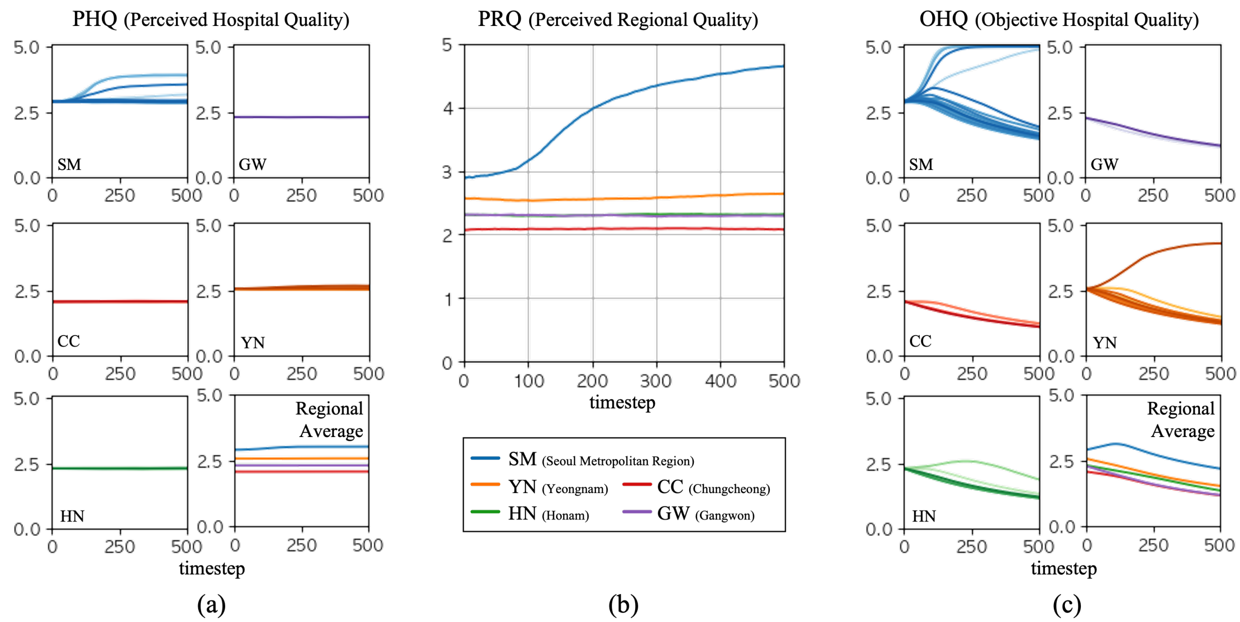


Figure 3: (a) Population-averaged PHQ of each hospital within each region over time (b) population-averaged PRQ for each region over time (c) population-averaged OHQ for each hospital within a region.

3.1.1 Local Dominance

A notable finding in the simulation results is that only in certain regions, a limited number of hospitals exhibit sharp increase of OHQ. In Figure 3(c), we observe such patterns for SM and YN; in the SM region, OHQ for four hospitals quickly converge to the maximum value while the rest of the hospitals exhibit decreasing OHQs. Likewise, in the YN region, one hospital reaches OHQ value of 4 with the OHQ of all other hospitals decreasing over time. We refer to this phenomenon as *Local Dominance*, wherein a small subset of leading hospitals attract most of the local patients and, as a consequence, grow in their OHQ.

This pattern emerges from a positive feedback loop of *scale effect*. As a hospital attracts a large volume of patients within a region, it benefits from stronger scale effects than the other hospitals in the region, resulting in the greater improvement in its OHQ. This quality improvement then enhances the hospital's PHQ for the patients through direct and indirect experiences – *Quality Recognition* and *Word-of-Mouth*, respectively. The higher PHQ of the hospital further boosts its patient inflow, which in turn leads to an even greater increase in the OHQ of the hospital. Meanwhile, other local hospitals are unable to sustain sufficient patient volume, and their OHQ stagnate or even decline. This reinforcing loop renders the leading hospitals gain a near-monopoly in their region.

3.1.2 Global Dominance

An interesting feature about the *Local Dominance* pattern is that it occurs only in certain regions. In the current simulation, local dominance is observed only in SM and YN, and no hospital captured the position of a leading hospital. In these regions, too many patients are drawn away to other areas, preventing local hospitals from having sufficient patient inflow to exhibit the loop of positive scale effect. This is particularly due to large metropolitan regions (e.g., SM) attracting a significant share of patients. Recall that PHQ of a hospital contributes to PRQ of the region it is located in, as well demonstrated in Figure 3(b) for the SM region, and that patients first choose a region they will seek care from based on PRQ values. Thus, once leading hospitals emerge in a major metropolitan region, they begin to attract not only local residents but also patients from neighboring regions, leading to what we call *Global Dominance*.

An illustrative example is the HN region, shown in Figure 3(c). In the HN region, OHQ of one hospital increases at the beginning, but starts to decrease from around time step 250, failing to maintain its local dominance. This is most likely because the PRQ of SM grew rapidly (Figure 3) to overcome the distance barrier and, as a result, the SM region attracts an increasing share of HN patients. Consequently, patient inflow to HN's leading hospital drops below the level needed to sustain positive scale effect, causing OHQ to decline. This example illustrates that an initial emergence of a hospital with upward OHQ in a region does not necessarily lead to the full establishment of *Local Dominance* if it encounters a stronger dominance in another region.

3.1.3 Asymmetric Quality Recognition

An additional observation is that the trajectories of PHQ and PRQ do not fully align with the trends in OHQ. This discrepancy arises because quality recognition is driven by hospital utilization among diagnosed patients, which in turn depends on the choice probabilities assigned to each hospital and region. Hospitals and regions with higher perceived quality (PQ) attract more patients, resulting in greater utilization and more frequent updates to public perception. In contrast, hospitals with lower PQ remain underutilized and less visible, limiting opportunities for perception adjustment. We refer to this dynamic as *Asymmetric Quality Recognition*.

Asymmetric Quality Recognition manifests at both the PHQ and PRQ levels. At the PHQ level, within the SM region, only the four leading hospitals show rising PHQ trends. If these hospitals receive even a slight opportunity early in the simulation to signal their improving OHQ to patients, that marginal increase in PHQ leads to higher choice probabilities, which in turn creates more opportunities to further expose their improving quality to patients. In contrast, hospitals with lower PHQ experience little to no utilization, meaning that even if their OHQ changes, patients are unlikely to notice. In other words, poorly perceived hospitals become “locked in” to their reputations, making it difficult to reverse negative perceptions, even with facility upgrades or quality improvements.

At the PRQ level, SM is the only region that shows a clear increase (Figure 3(b)), primarily because a substantial share of patients utilize hospitals in SM and subsequently recognize their quality. This upward trajectory is largely driven by the region's leading hospitals: patients who choose SM often visit one of the high-PHQ hospitals, and their high-OHQ experiences elevate the perceived quality (PRQ) of the entire region. As a result, SM's PRQ surpasses the average OHQ of its hospitals, pulled upward by a few standout institutions – an effect we refer to as *PRQ traction*. This phenomenon is reinforced by the total volume of patient inflow to the region, meaning it works more strongly in regions with already high PRQ. Consequently, high-PRQ regions benefit disproportionately from this Asymmetric PRQ Traction, which further amplifies Global Dominance by widening the PRQ gap across regions.

3.1.4 Implications for Patient Concentration

Our analysis suggests that, to mitigate patient concentration, fostering *Local Dominance* within each region is crucial. Regions lacking a leading hospital often face the gradual degradation of their healthcare infrastructure, while successful establishment of local dominance helps sustain local patient utilization.

Indeed, one can argue that, from the perspective of the regionalized healthcare system, the emergence of a leading hospital is desirable as it enhances the quality of care available locally, and reduces patients' incentives to incur high travel costs by seeking better care in other regions.

However, when such local dominance emerges in major metropolitan areas, in the rise of major leading hospitals likely leads to *Global Dominance*, drawing patients away from smaller regions and neutralizing the effect of local dominance in the smaller regions. Compounding this effect, *Asymmetric Quality Recognition* disproportionately amplifies the visibility and perceived success of leading hospitals and regions, making it increasingly difficult for others to compete. Furthermore, leading hospitals in high-PRQ regions elevate regional perception through *PRQ traction*, pulling up the overall PRQ and further widening the gap between regions – thereby accelerating the dynamics of global dominance.

We infer that regions with smaller populations or close proximity to major metropolitan areas are particularly susceptible to be affected by the global dominance. A larger population base increases the likelihood of sustaining the over-threshold patient volume necessary to nurture a leading hospital. Greater distance from metropolitan centers raises travel costs and discourages outmigration, thereby mitigating the effects of global dominance.

3.2 Analysis on Parameters' Influence

The parameters in our simulation can influence the strength of the four quality interaction mechanisms, thereby shaping patient outmigration patterns. We perform a sensitivity analysis by systematically varying each parameter within its predefined range and measuring changes in the *degree of patient outmigration*, defined as the area under the curve (AUC) of population-averaged outmigration probability over time. Details are provided in Appendix D.

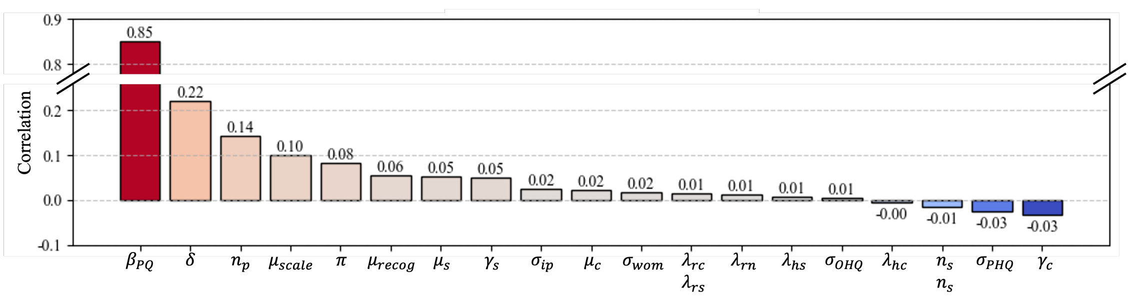


Figure 4: Correlation between simulation parameters and degree of outmigration

Figure 4 presents the correlation between each parameter and outmigration. Each of these parameters contributes to the *acceleration of global dominance in the SM region*, thereby diminishing the likelihood of local dominance emerging in non-SM regions. Parameters such as β_{PQ}, n_p, and μ_{scale} correlate positively with outmigration, accelerating global dominance in the SM region and lowering the chance of local dominance elsewhere. A high β_{PQ} ($\beta_{\text{PRQ}}, \beta_{\text{PHQ}}$) places greater weight on perceived quality, boosting inflow to SM and weakening potential leading hospitals in other regions. A larger δ eases outmigration by reducing distance penalties. An increased μ_{scale} accelerates OHQ growth in SM once sufficient patient inflow is reached. Lastly, a higher n_p leads to more frequent perception updates, further reinforcing global dominance in SM.

3.3 Information Provision Policy

3.3.1 Policy Configuration

As discussed previously, the interplay among different quality constructs generates various emergent phenomena, inevitably contributing to patient concentration. In particular, *asymmetric quality recognition* exacerbates patient concentration by widening the gap between perceived quality (PQ) and objective quality (OQ). Therefore, we explore how an intervention aimed at artificially reducing the PQ-OQ gap influences the overall system and ultimately mitigates patient concentration. To reduce the gap between quality constructs, we implement an *information provision policy* (IPP) in the simulation. IPP directly intervenes in the quality feedback loop by providing individuals with information about the Objective Hospital Quality (OHQ). Under this policy, each individual's PHQ and PRQ are replaced by the disclosed OHQ values. We examine two distinct policy alternatives in this study: *hospital-level IPP* that reveals the OHQ of each hospital, thereby influencing PHQ directly; and *regional-level IPP* that discloses the average OHQ of all hospitals within each region, thereby substituting each individual's PRQ.

In the simulation experiments, at each simulation time step, we let a subset of diagnosed cancer patients, as well as a smaller subset of other individuals, acquire this information and update their PQ accordingly. We then evaluate whether this mechanism exacerbates or mitigates the *degree of patient outmigration*, assessing the overall effectiveness of the policy. Furthermore, we carry out a analysis on parameters' inluence on these effectiveness measures, in order to understand how changes in simulation parameters steers each policy alternative's impact. We measure policy effectiveness as the reduction in the outmigration AUC relative to the corresponding simulation without information provision. Details of policy implementation and experiment design can be found in Appendix E.

3.3.2 Policy Assessment Results

The optimal policy alternative for minimizing the degree of outmigration varied across different parameter configurations, as the effectiveness of each option—Hospital-level IPP and Regional-level IPP—depended on the specific parameter settings. Specifically, hospital-level IPP is proved to be more effective in mitigating outmigration under conditions favorable to local dominance in non-SM regions—i.e., in an *optimistic environment*. Its effectiveness improves with lower δ, higher π and μ_{scale}, all of which align with the factors that encourage local dominance. In such an environment, hospital-level IPP reveals the individual OHQ values of each hospital, allowing patients to know the declinding OHQ of non-leading hospitals (which was veiled by asymmetric quality recognition under circumstances without IPP). As a result, more patients are concentrated to the potential leading hospital with high OHQ, reinforcing local dominance and retaining more patients locally, ultimately reducing outmigration.

Conversely, regional-level IPP is more effective in a *pessimistic environment*, where *global dominance* is likely to emerge and local dominance cannot easily take hold. In these settings, the leading hospitals in SM grow rapidly, pull the PRQ upward via *PRQ traction*, and attract patients from other regions. Regional-level IPP counters this by disclosing the average OHQ of each region, thereby preventing SM's *overestimation* of PRQ due to PRQ traction. The average OHQ in SM typically drops once non-leading hospitals are factored in (see regional average plot of OHQ in Figure 3(c)), which reduces the PRQ of SM.

In summary, hospital-level IPP is preferable when conditions support local dominance, while regional-level IPP is advantageous under scenarios favoring global dominance. A more detailed results and discussions on the policy effectiveness can be found in Appendix F.

4 CONCLUSION

In this paper, we examined the problem of hospital bypassing and utilization concentration by developing an agent-based simulation framework that captures the co-evolution of objective quality (OQ) and perceived quality (PQ) through four key interaction mechanisms: *Preferential Hospital Choice*, *Scale Effect*, *Quality Recognition*, and *Word-of-Mouth*. Through this framework, we observed how these feedback loops give rise to system-level emergent phenomena, including *Local Dominance*, *Global Dominance*, and *Asymmetric Quality Recognition*. Among these, local dominance – the emergence of one or a few leading hospitals within a region – stands out as a critical dynamic for sustaining local healthcare capacity and reducing outmigration. Conversely, global dominance arises when a strong metropolitan region attracts excessive patient inflows from other areas, impeding the development of non-metropolitan leading hospitals and exacerbating regional disparities.

Our simulation results highlight the importance of promoting local dominance in non-metropolitan regions as a strategy to mitigate patient concentration and foster equitable access across the healthcare system. Rather than uniformly raising the quality of all hospitals, a more effective approach may be to concentrate resources and patient volume into one or two high-potential hospitals per region. If these hospitals can enter and sustain the positive feedback loop of the scale effect, they become viable alternatives to distant metropolitan providers for patients. Addressing patient concentration problem at the national level may require each region to pursue a form of *local tiering*, strategically cultivating strong institutions to ensure system-level sustainability.

We also evaluated an *Information Provision Policy* (IPP) aimed at narrowing the gap between perceived and objective quality by disclosing OHQ to patients. Hospital-level IPP tends to be more effective in optimistic scenarios, where non-SM regions can still develop local dominance. In contrast, regional-level IPP is more advantageous in pessimistic scenarios where global dominance is already entrenched.

Several directions for future research remain. First, model fidelity could be enhanced by incorporating additional complexities — such as heterogeneity in patient decision-making, explicit capacity constraints, or more nuanced modeling of scale effects. Second, while our model focuses on cancer care in South Korea — a context where patient choice plays a significant role —, future extensions could explore other disease types or healthcare systems, including smaller-scale providers such as secondary or primary care facilities. Third, alternative forms of IPP could be explored; for instance, while our regional-level policy uses average OHQ as the disclosure metric, other regional indicators may yield different effects.

Despite these limitations, our study provides a valuable framework for analyzing the dynamic interplay between perceived and objective quality, the self-reinforcing mechanisms that drive regional disparities, and the policy levers that may help rebalance patient flows. We envision this model-based approach will inform future research and guide evidence-based policy design in healthcare systems — particularly in contexts like South Korea's, where patient autonomy in hospital choice is highly emphasized.

ACKNOWLEDGMENTS

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A WORD-OF-MOUTH MECHANISM

Word-of-Mouth (WOM) mechanism involves patients' perceived qualities (PQs) gradually converging and co-evolving through social interactions. WOM comprises two components: direct interactions and indirect interactions.

Direct WOM occurs when individuals share their hospital experiences with neighbors, influencing each other's PQ values. We distinguish two types of individuals:

- Cancer patients : Agents who have been diagnosed with cancer at time step t, and have first-hand hospital experience. Their influence is stronger and one-way; they impart updates to others but do not receive them.
- Susceptible : Agents who have not been diagnosed with cancer in the current step. Their influence is weaker and two-way; they both give and receive updates from neighbors.

Each agent has a set of neighbors determined by proximity, with a distance decay factor (δ) reducing the WOM effect over greater distances.

Indirect WOM represents media and public sentiment. It shifts each agent's PRQ toward the mean PRQ of the region where they reside. We assume that this indirect effect does not influence the PHQ, as large-scale media or public opinion effects are unlikely to operate at the granular level of individual hospitals.

Let $PHQ^t_{i,h}$ denote the perceived hospital quality of agent i with respect to hospital h at time step t. After one simulation step, the updated value $PHQ^{t+1}_{i,h}$ is calculated as follows.

$$PHQ^{t+1}_{i,h} = PHQ^t_{i,h} + C_{ih}(t) + S_{ih}(t) + \varepsilon^t_{i,h} \tag{9}$$

$$C_{ih}(t) = \sum_{j \in \Theta^c_i} \mu_{hc}(PHQ^t_{j,h} - PHQ^t_{i,h}) \times 1_A(|PHQ^t_{j,h} - PHQ^t_{i,h}| \leq \lambda_c) \times e^{-\delta d_{ij}} \tag{10}$$

$$S_{ih}(t) = \sum_{j \in \Theta^s_i} \mu_{hs}(PHQ^t_{j,h} - PHQ^t_{i,h}) \times 1_A(|PHQ^t_{j,h} - PHQ^t_{i,h}| \leq \lambda_s) \times e^{-\delta d_{ij}}, \tag{11}$$

$C_{ih}(t)$ denotes the influence of neighboring cancer patients, $S_{ih}(t)$ is the influence from susceptible neighbors, and $\varepsilon^t_{i,h}$ is Gaussian-distributed random noise with standard deviation σ_{wom}. Equation (10) shows how the cancer patients' direct influence is calculated, where Θ^c_i is the set of cancer patients among i's n_c nearest neighbors, μ_{hc} is a WOM strength parameter, 1_A is an indicator function that is 1 when the absolute difference is within λ_c, and $e^{-\delta d_{ij}}$ is the distance decay factor. Cancer patients only *give* updates, so they do not receive any direct updates from others. The susceptible contribution is calculated as equation (11), where Θ^s_i is the set of susceptible neighbors of i, μ_{hs} is set to be smaller than μ_{hc}, λ_s is the threshold for confirmation bias among susceptible agents, and $e^{-\delta d_{ij}}$ remains the same distance decay term. This influence is two-way, meaning susceptible agents update each other.

For $\text{PRQ}^t_{i,r}$, the update equation includes both direct and indirect interactions:

$$PRQ^{t+1}_{i,r} = PRQ^t_{i,r} + C_{ir}(t) + S_{ir}(t) + N_{ir}(t) + \varepsilon^t_{i,r} \tag{12}$$

$$C_{ir}(t) = \sum_{j \in \Theta^c_i} \mu_{rc}\big(PRQ^t_{j,r} - PRQ^t_{i,r}\big) \times 1_A\Big(|PRQ^t_{j,r} - PRQ^t_{i,r}| \leq \lambda_c\Big) \times e^{-\delta d_{ij}} \tag{13}$$

$$S_{ir}(t) = \sum_{j \in \Theta^s_i} \mu_{rs}\big(PRQ^t_{j,r} - PRQ^t_{i,r}\big) \times 1_A\Big(|PRQ^t_{j,r} - PRQ^t_{i,r}| \leq \lambda_s\Big) \times e^{-\delta d_{ij}} \tag{14}$$

$$N_{ir}(t) = \mu_{rn}\Big(\big(\frac{1}{|\Theta_{r_i}|} \sum_{j \in \Theta_{r_i}} PRQ^t_{j,r}\big) - PRQ^t_{i,r}\Big) \tag{15}$$

Here, $C_{ir}(t)$ and $S_{ir}(t)$ follow the same structure as Equations (10) and (11), replacing $PHQ^t_{j,h}$ with $PRQ^t_{j,r}$ and using parameters μ_{rc} and μ_{rs}. The indirect term $N_{ir}(t)$ is calculated as Equation (15), where Θ_{r_i} is the set of agents residing in the same region as i, and μ_{rn} decides how strongly an individual converges to the regional mean PRQ. No distance decay is applied here, reflecting a mass-media or community-wide effect.

All parameters introduced above are assigned baseline values to form a *Base Parameters*, and are subject to analyze the impact of their variation. We also reuse the same distance decay parameter δ from the hospital choice model for consistency.

B BASELINE PARAMETER SETTING

This appendix describes how we established the baseline parameter setting for our simulation. We aimed to replicate the current trend of patient concentration in the Seoul Metropolitan region, reflecting actual hospital-choice patterns observed in Korea. To this end, we focused on specifying the initial perceived regional quality (PRQ) values and the hospital choice parameters, namely $\beta_{\mathrm{PRQ}}, \beta_{\mathrm{d}}, \delta$. Detailed process of calibrating these parameters discussed in Appendix C.

All agents and hospitals begin with initial values of perceived and objective quality generated around a baseline PRQ for each region. Specifically, every hospital's OHQ is sampled from a Gaussian distribution centered on its region's baseline PRQ (standard deviation σ_{OHQ}), and each individual's PRQ is similarly derived from the same baseline with added Gaussian noise (σ_{PRQ}). Individual PHQ values are then obtained by adding further noise (σ_{PHQ}) around that region's baseline PRQ. Consequently, hospitals and individuals start with values near a common regional mean but exhibit random (gaussian-distributed) variations.

Parameters not directly tied to the initial outmigration pattern—such as μ_{scale}, the number of diagnosed patients per time step n_p, or the strength of word-of-mouth interactions—were assigned appropriate default values arbitrarily. We then varied these in subsequent policy experiments to evaluate their impact on the degree of patient outmigration. A comprehensive list of parameter settings is provided in Table 1.

C INITIAL PARAMETER CALIBRATION

This appendix describes how we calibrated the initial parameters $\beta_{\mathrm{PRQ}}, \beta_{\mathrm{d}}, \delta$ of the simulation, to the real-world dataset of South Korea. In this simulation, hospital choices are determined through the *Hospital Choice* mechanism, employing two-step hierarchical logit model (Equations (2)–(4)), where each patient first chooses a region and then a hospital within that region. To make the initial choice patterns closely reflect real-world data, we calibrated initial PRQ (Perceived Regional Quality) values for each region as well as the utility function parameters $\beta_{\mathrm{PRQ}}, \beta_d, \delta$ using a *Genetic Algorithm (GA)*.

We compiled data from 16,664 Korean cancer patients between 2008 and 2017, drawing on a dataset created by the relevant study of our research team. Each record contains the patient's region of residence and the region of the hospital where their first cancer surgery was performed. To match the geographical granularity of our simulation, we reorganized the dataset into five regions for our simulation (SM, YN, HN, CC, and GW) and generated a 5×5 Origin-Destination (OD) matrix. Each entry $(r_1 \to r_2)$ indicates the proportion of patients residing in region r_1 who traveled to region r_2 for surgery. This OD matrix captures the observed inter-regional flow of surgical patients and serves as our primary empirical target for calibration. Subsequently, we derived region-specific RI (regional inflow/outflow indicators) and CI (concentration indices) from the OD matrix, obtaining separate 5×5 matrices for RI and CI. These two matrices were then combined into a single 5×10 RI-CI matrix, which constituted our final calibration target.

We include the following eight parameters in the calibration:

- Five initial PRQ_r values ($2 \leq \mathrm{PRQ}_r \leq 3$), one for each region
- β_{PRQ}: coefficient for the PRQ term in the utility function
- β_d: coefficient for the travel distance term $\exp(\delta \cdot d)$
- δ: the exponent parameter controlling the distance decay effect

Additionally, at the initial simulation state, each agent (patient) is assumed to hold the same PRQ value for a given region, i.e., PRQ_r is identical across all agents for region $r \in \{\text{SM}, \text{YN}, \text{HN}, \text{CC}, \text{GW}\}$. Once a particular set of eight parameter values is inserted into the simulation, we compute, for the first time step (i.e., before patients update their perceptions through personal experience or word-of-mouth), the probability that each agent chooses each of the five regions. Summing these probabilities over the entire population yields a simulation-based 5×10 RI-CI matrix, analogous to the one observed in the real-world data. The goal is to make this simulated matrix as close as possible to the empirical matrix, by minimizing the following root mean squared error (RMSE):

$$\min_{\{\text{PRQ}_r, \beta_{\text{PRQ}}, \beta_d, \delta\}} \sqrt{\sum_{r_1} \sum_{r_2} \left(\left(\widehat{RI}^{\text{sim}}_{r_1,r_2} - RI^{\text{obs}}_{r_1,r_2} \right)^2 + \left(\widehat{CI}^{\text{sim}}_{r_1,r_2} - CI^{\text{obs}}_{r_1,r_2} \right)^2 \right)},$$

where $RI^{\text{obs}}_{r_1,r_2}$ and $CI^{\text{obs}}_{r_1,r_2}$ represent the observed metrics for inflow/outflow and concentration between regions r_1 and r_2, while $\widehat{RI}^{\text{sim}}_{r_1,r_2}$ and $\widehat{CI}^{\text{sim}}_{r_1,r_2}$ are derived from the simulated OD data.

We solve this optimization problem using a GA, in which each chromosome consists of eight parameters, and each generation has 100 chromosomes. The initial population of the GA spans a broad range of parameter values, and standard GA operations (selection, crossover, mutation) are iteratively applied to reduce the RMSE. By approximately the 7,000th generation, the algorithm converges. Figure 5 illustrates an example of the minimum RMSE trajectory across generations.

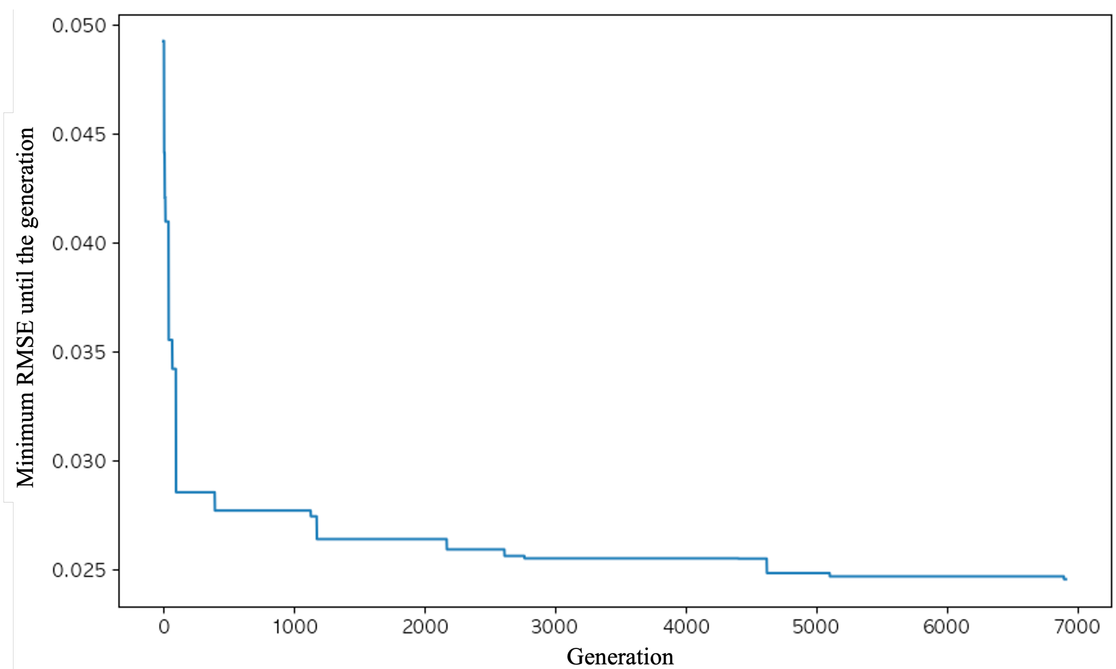

Figure 5: GA Convergence Curve (Minimum RMSE by Generation)

After convergence, we collect the top 100 chromosomes with the lowest RMSE from the entire generations, and plot their distributions in boxplots, as shown in Figure 6. Notably, the Seoul Metropolitan (SM) region often exhibits the highest PRQ_{SM}, while other large urban areas (e.g., YN) also converge to relatively higher PRQ values. This matches the known context of regional disparities in South Korea's hospital utilization.

We then take the median values from these top 100 chromosomes for each parameter and adopt them as the final initial parameter settings for the base scenario. Specifically, these values form the initial regional PRQs and the coefficients $\beta_{\text{PRQ}}, \beta_d, \delta$ in Equations (2)–(4).

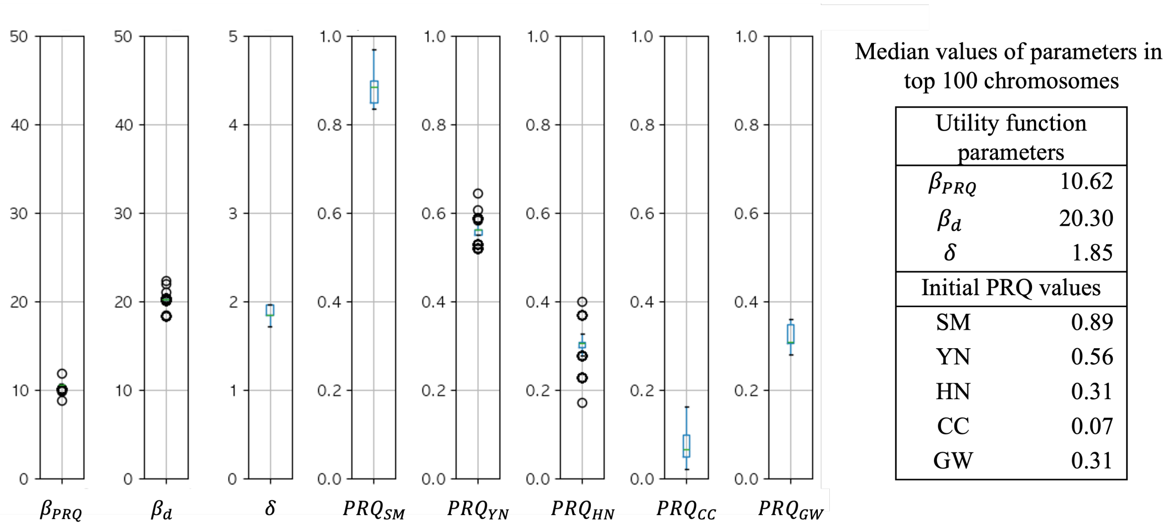

Figure 6: Boxplots of Parameter Distributions for the Top 100 Chromosomes

For the hospital-level choice, we apply the same parameters $\beta_{\text{PRQ}}, \beta_d, \delta$ but introduce a separate scale parameter π (see 2.2.1) to adjust the level of random fluctuations within each region. Finally, these parameter values serve as the baseline configuration in both the base scenario and subsequent policy experiments.

Table 1: Parameter values for base scenario

Category	Parameter	Value	Category	Parameter	Value
Initial PRQ	PRQ_{SM}	0.89	Quality Recognition	μ_{recog}	0.8
	PRQ_{YN}	0.56		σ_{recog}	0.05
	PRQ_{HN}	0.31	Word-of-Mouth	n_s	10
	PRQ_{CC}	0.07		n_c	50
	PRQ_{GW}	0.31		μ_{hc}	0.8
	σ_{PRQ}	0.02		λ_c	1.5
Initial PHQ	σ_{PHQ}	0.02		μ_{hs}	0.2
Initial OHQ	σ_{OHQ}	0.02		λ_s	1.5
Hospital Choice	$\beta_{\text{PRQ}}, \beta_{\text{PHQ}}$	10.62		σ_{wom}	0.01
	β_d	20.30		μ_{rc}	0.8
	δ	1.85		μ_{rs}	0.1
	π	1.0		μ_{rn}	0.1
Scale Effect	μ_{scale}	1.0	New patients	n_p	28

D ANALYSIS ON PARAMETERS' INFLUENCE

In addition to the empirically calibrated initial parameters, we arbitrarily assigned appropriate default values to all other parameters to form our baseline setting. These parameters directly or indirectly influence the strengths of the quality interaction mechanisms, ultimately affecting the *degree of patient outmigration*. The objective of our sensitivity analysis is to quantify how changes in these parameters alter the outmigration patterns.

Table 2: Parameter ranges for LHS sampling

Category	**Parameter**	**Lower bound**	**Upper bound**
Initial Quality	σ_{PRQ}	0.00	0.05
	σ_{PHQ}	0.00	0.05
	σ_{OHQ}	0.00	0.05
Hospital Choice	β_{PRQ}, β_{PHQ}	0.0	20.0
	δ	1.0	3.0
	π	0.0	2.0
Scale Effect	μ_{scale}	0.0	2.0
Quality Recognition	μ_{recog}	0.3	1.0
	σ_{recog}	0.0	2.0
Word-of-Mouth	n_s	5	20
	n_c	10	200
	μ_{hc}	0.3	1.0
	λ_c	0.3	3.0
	μ_{hs}	0.0	0.5
	λ_s	0.3	3.0
	σ_{wom}	0.00	0.05
	μ_{rc}	0.3	3.0
	μ_{rs}	0.0	0.5
	μ_{rn}	0.0	0.3
New Patients	n_p	5	100
Information Provision	γ_c	0.01	1.5
	γ_s	0.0	0.2
	σ_{ip}	0.00	0.05

To conduct this analysis, we employed a *global sensitivity analysis (GSA)* by sampling the parameter space over sufficiently broad ranges. Table 2 lists the sampling range for each parameter. We generated 1,000 distinct parameter sets via *Latin Hypercube Sampling (LHS)*, ensuring a relatively uniform exploration of the parameter space. For each sampled set, we executed the full simulation and computed the resulting *degree of outmigration*, defined as the area under the curve (AUC) of the population-averaged outmigration probability over time. Outmigration probability is calculated for each individual as the probability of choosing a region other than one's own.

Although $\beta_{\text{PRQ}}, \beta_{\text{PHQ}}$, and δ were already calibrated to real-world data for the baseline scenario, we included them in the sampling process—holding β_d fixed—to observe how varying the patients' utility weights for perceived quality and distance would affect the system dynamics. We also sampled parameters associated with the *Information Provision Policy* (namely γ_c, γ_s, and σ_{ip}), whose implementation details are provided in Appenndix E.

Finally, upon completing all 1,000 simulation runs, we correlated each parameter's sampled values with the resulting *degree of outmigration* to assess how sensitive outmigration patterns are to changes in each parameter. This correlation-based analysis helps observe which factors most strongly drive patient flows out of their home regions.

E CONFIGURATION OF INFORMATION PROVISION POLICY

The Information Provision Policy (IPP) directly intervenes in the quality feedback loop by disclosing objective quality (OHQ) information to individuals, thereby influencing their perceived quality (PQ). Our goal is to determine whether and under what conditions such a policy helps mitigate the patient concentration problem.

We examine three policy alternatives: **Default** (no policy), **Hospital-level IP**, and **Regional-level IP**. Even when an IPP is implemented, we assume not all individuals acquire and incorporate this information into their perceptions. Specifically, at each simulation time step, a fraction γ_c of the diagnosed patients (i.e., those who seek treatment during that step) is randomly selected to observe the relevant OHQ data, and a fraction γ_s of the rest of the individuals is likewise chosen to receive the same information. We also introduce random noise to reflect the possibility that individuals do not fully understand the implications of OHQ on their healthcare outcomes.

In the *Hospital-level* approach, OHQ values of each hospital are revealed, directly affecting patients' PHQ as follows:

$$PHQ_{i,h}^{t+1} = OHQ_h^t + \varepsilon_{i,h,ip}^t \tag{16}$$

where $\varepsilon_{i,h,ip}^t$ is Gaussian-distributed noise with standard deviation σ_{ip}.

In the *Regional-level* approach, patients learn the average OHQ of all hospitals within a region, thereby substituting each individual's PRQ:

$$PRQ_{i,r}^{t+1} = \overline{OHQ_r^t} + \varepsilon_{i,r,ip}^t \tag{17}$$

where $\overline{OHQ_r^t}$ is the mean OHQ of all hospitals in the region r at time t, and $\varepsilon_{i,r,ip}^t$ is Gaussian noise with standard deviation σ_{ip}.

We assessed the impact of each IPP alternative under the 1,000 parameter sets described in Appendix D. For each parameter set, we ran three simulations (Default, Hospital-level IP, and Regional-level IP) and measured the resulting degree of outmigration (the AUC of population-averaged outmigration probability). We then defined the *effectiveness of Hospital-level IPP* as the difference in outmigration AUC between the Default and Hospital-level simulations. Positive value of policy effectiveness indicates that outmigration decreased relative to the Default scenario. An equivalent definition applies for the effectiveness of Regional-level IPP.

By correlating these effectiveness measures with variations in each parameter, we performed a same GSA with Appendix D to see how different policy implementations fare under various conditions. Using 1,000 different parameter sets, we compared simulation results of three different alternatives of *information provision policy*: **Default** (no policy), **Hospital-level**, and **Regional-level**. In this way, our analysis clarifies when and why the Information Provision Policy may help alleviate patient concentration.

F ASSESSMENT RESULTS OF INFORMATION PROVISION POLICY

Figure 7 shows the impact of each simulation parameter on the effectiveness of hospital-level IPP. The optimal policy alternative (minimizing the degree of outmigration) varied under different parameter configurations, since each alternative (Hospital-level IPP and Regional-level IPP) proved more or less effective depending on the parameter setting. The second and third rows in Figure 4 show the correlation of each parameter with the effectiveness of the two policy alternatives.

F.1 Hospital-level IPP

Hospital-level IPP is proved to be more effective in mitigating outmigration under conditions favorable to *local dominance* in non-SM regions—i.e., in an *optimistic environment*. As shown in the Figure 7, its effectiveness improves with lower δ, higher π, and lower μ_{scale}, all of which align with the factors that encourage *local dominance*.

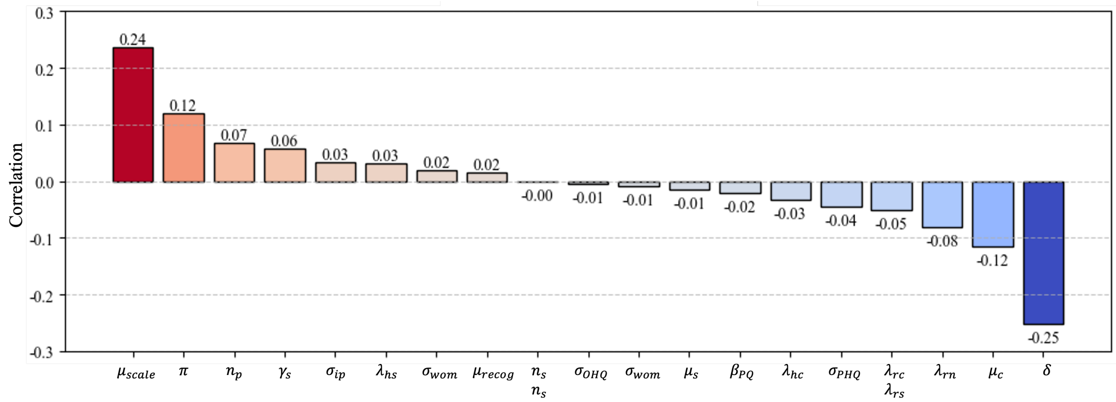

Figure 7: Correlation between simulation parameters and effectiveness of hospital-level IPP

A smaller δ increases the relative cost of traveling outside one's home region, raising local utilization and the possibility that at least one local hospital reaches the critical inflow needed to spark a positive feedback loop of scale effect. A higher π means that individuals choose hospitals within a chosen region more rationally, thus driving more people to *the best hospital* in that region (based on PHQ), amplifying *local dominance*. Meanwhile, a higher μ_{scale} provides better opportunities for potential leading hospitals to emerge in non-SM regions, under the condition of positive scale effect triggered.

In such an environment, hospital-level IPP reveals the *individual* OHQ values of each hospital. Under normal circumstances, *asymmetric quality recognition* might limit patients' knowledge to only a few well-known hospitals. With policy-based full disclosure, however, patients are also shown which non-leading hospitals have declining OHQ. As a result, more patients converge to the hospital with highest OHQ within the region, reinforcing local dominance and retaining more patients locally, ultimately reducing outmigration.

F.2 Regional-level IPP

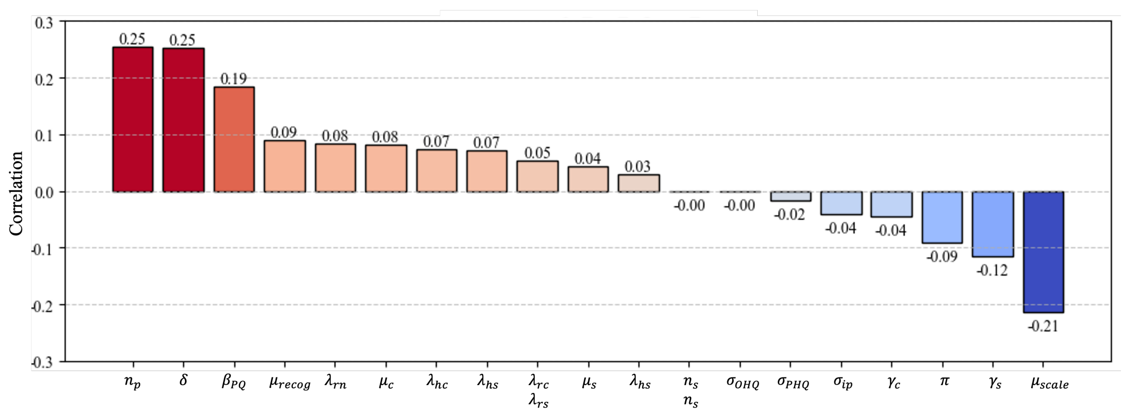

Figure 8: Correlation between simulation parameters and effectiveness of regional-level IPP

Figure 8 shows the impact of each simulation parameter on the effectiveness of regional-level IPP. Conversely, regional-level IPP is proved to be more effective in a *pessimistic environment*, where *global dominance* is likely to emerge and local dominance cannot easily take hold.

As illustrated in the third row of Figure 8, parameters that favor *global dominance* (e.g., high β_{PQ}, large δ, high n_p, as illustrated in 3.2) correlate positively with the effectiveness of regional-level IPP. A low π also weakens *local dominance*, as intra-regional hospital choices are more random; combined with a high μ_{recog} or strong WOM, SM's rising PRQ spreads quickly across the population, accelerating *global dominance*.

In these pessimistic settings, the leading hospitals in SM grow rapidly, pulls upward the PRQ via *PRQ traction*, and attract patients from other regions. *Regional-level IPP* counters this by disclosing the average OHQ of each region, thereby preventing SM's *overestimation* of PRQ due to PRQ traction. The average OHQ in SM typically drops once non-leading hospitals are factored in (see Figure 3(c)), which reduces SM's regional PRQ. Other regions also see a decline, but since SM enjoys disproportionately high PRQ traction, the relative reduction in SM's PRQ is larger and outmigration is alleviated. In essence, by forcing patients to update PRQ based on the region's *mean* OHQ rather than the handful of best hospitals (smooth maximum), the policy dampens PRQ traction in SM and mitigates *global dominance*.

Overall, these findings suggest that each policy approach works best under different conditions: hospital-level information provision is more effective when non-SM local dominance is feasible, whereas regional-level provision is more beneficial when global dominance is already favored.

APPENDIX

The full manuscript, including all appendices and the simulation source code, is available at: https://github.com/jungwoo415/Outmigration_ABM/

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