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

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ABSTRACT

We present an agent-based model that explores how objective quality (OQ) and perceived quality (PQ) co-evolve in a free-choice healthcare system, using South Korea as a salient case. We implement four interaction mechanisms (Hospital Choice, Scale Effect, Quality Recognition, and Word-of-Mouth) to configure a feedback loop between OQ and PQ: as concentration of choice elevates a hospital's OQ through scale effect, utilization in turn updates and disseminates PQ via quality recognition and Word-of-Mouth. We identify three emergent phenomena-Local Dominance, Global Dominance, and Asymmetric Quality Recognition—and suggest that promoting "local tiering" strategy in non-metropolitan regions is critical to mitigating excessive patient concentration to globally dominant regions. We also examine an Information Provision Policy (IPP) with two distinct alternatives (hospital-level and regional-level), each performing better under opposite conditions. We hope this model-based approach enhances deeper understanding of OQ–PQ dynamics, needed to mitigate nationwide healthcare system 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 selection 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). This behavior is especially prevalent among patients with serious chronic conditions such as cancer and presents significant systemic challenges by creating system-level inefficiencies. 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 PHQ as patients experience a hospital's OHQ 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 details the structure and implementation of the simulation model and its components, including parameter configuration and experimental design. Section 3 then examines the emergent phenomena arising from the interlinked quality dynamics and discusses how they drive system-level patient concentration. In addition, a comprehensive sensitivity analysis is presented to illustrate how parameter variations influence outmigration patterns and policy outcomes. We also assess the effectiveness of the Information Provision Policy by describing its conceptual framework and reporting findings from policy experiments. Finally, Section 4 concludes this work by summarizing the contributions and limitations of this study and proposes directions for future research.

2 METHODS

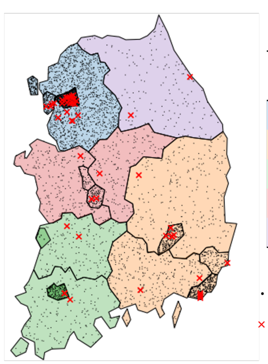
2.1 Simulation Configuration

Our agent-based simulation models the dynamics between individuals, who make hospital 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 divergence in quality measures over time, facilitating observation of intensified patient concentration phenomena as the simulation progresses. 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 and geographical context including distance to hospitals (*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.

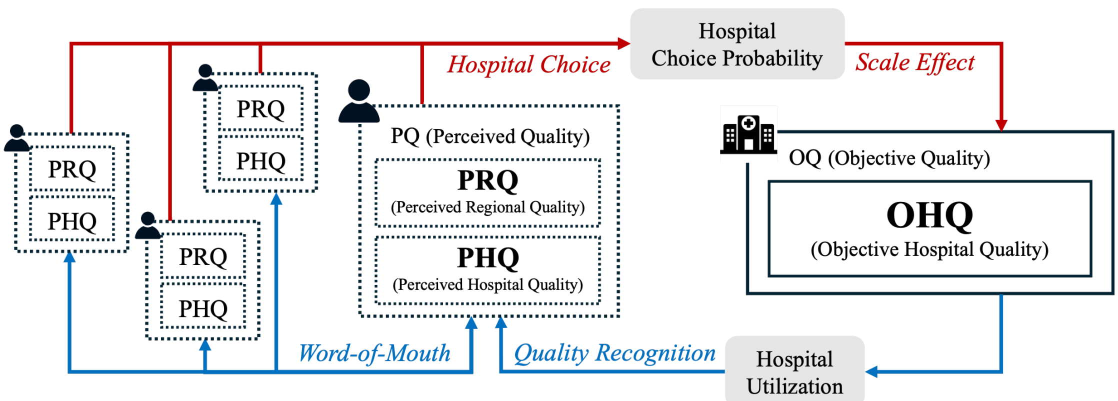


Figure 2: Quality interplay mechanisms and feedback loop

2.2.1 Hospital Choice

At each time step, every individual calculates choice probabilities for each hospital based on their perceived quality (PQ). 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* 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: $R = \{SM, YN, HN, CC, GW\}$. The observed utility for individual i selecting region $r \in R$ 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., $\pi \to \infty$, 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 whether hospital h attracts more or fewer patients than 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:

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

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

where OHQ_h^t is the objective quality of hospital h at time t, $\mathrm{PHQ}_{i,h}^t$ 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 **??**.

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 [What about PHQ and OHQ?]), which determine the 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 parameters were assigned appropriate initial values and are later subjected to sensitivity analysis.

2.3.2 Simulation Procedures

The simulation proceeds through the following iterative steps:

1. Initialize perceived quality measures (PHQ, PRQ) and objective hospital quality (OHQ) for all individuals and hospitals. [Haven't PHQ and PRQ been set in the calibration step?]
2. At each timestep t:
   (a) Each patient i calculates their choice probabilities for regions and subsequently for hospitals following the implemented *hospital choice* process, based on their current perceived qualities (PHQ, PRQ) and distance to hospitals. [IS THERE A SEQUENCE ISSUE HERE? DON'T WE JUST COMPUTE $P_i(h) = P_i(r_h) * P_i(h|r_h)$ and SUM OVER i TO OBTAIN $P(h)$?]
   (b) Aggregate the hospital choice probabilities across the entire population to update each hospital's OHQ based on the *scale effect* mechanism, as specified in Eq.(6).
   (c) A predefined number of agents (n_p) are diagnosed with cancer, selecting hospitals according to their calculated choice probabilities, experiencing hospital quality firsthand, and updating their perceived qualities via the *quality recognition* mechanism.[If only n_p uses hospitals at time t,

how come we update OHQ based on $P(h)$? I guess this is because we define the scale effect as a function of surplus "choice probability" not of actual volume, so it is understandable. Yet, it is a little confusing because it sounds like OHQ is updated "before" patients actually visit the hospitals...]

(d) All agents update their perceived qualities by sharing experiences through direct social interactions and indirect regional influences according to the *word-of-mouth* mechanism.

3. Repeat Step 2 until the designated number of simulation cycles (500 timesteps) is completed.

2.3.3 Sensitivity Analysis

The parameters in our simulation directly or indirectly affect the intensities of the four quality interaction mechanisms implemented. To investigate how they steer the pattern of patient outmigration and concentration, we conduct a sensitivity analysis by varying each parameter within its assigned range. We then examine how these variations alter the *degree of patient outmigration*. We define the *degree of outmigration* as the area under the curve (AUC) of the population-averaged outmigration probability over time. Detailed procedures for the sensitivity analysis are provided in Appendix **??**.

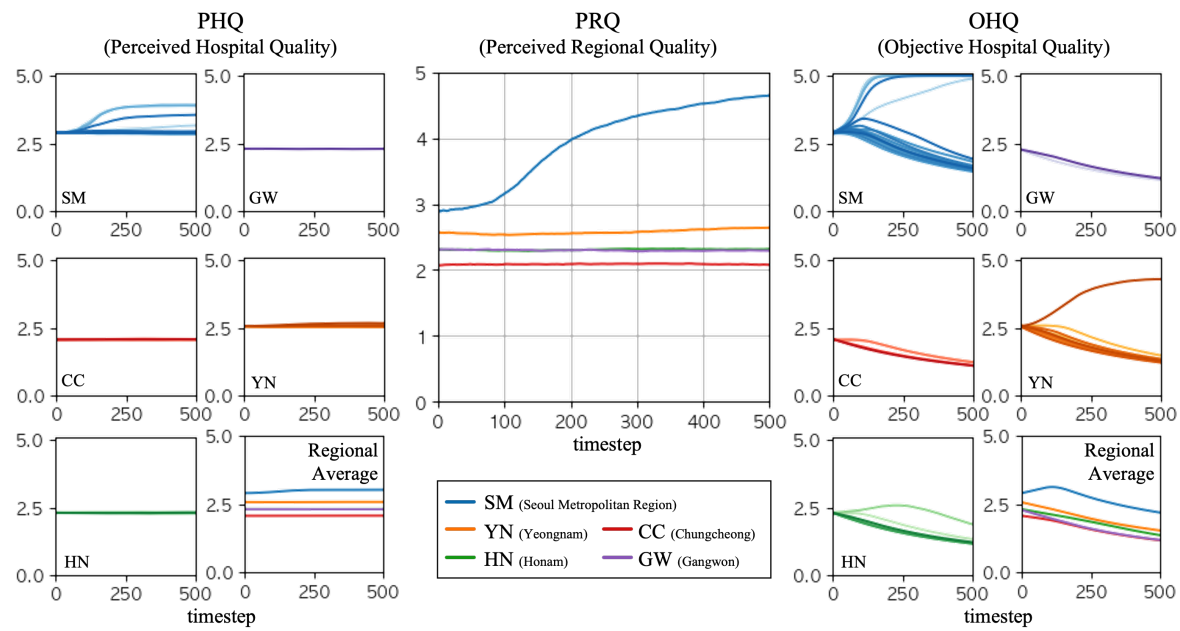


Figure 3: Trajectories of Quality Constructs under Baseline Setting

The left panels (PHQ graphs) show the average population-averaged PHQ of each hospital within each region, over time. They also include a "Regional Average" line representing the mean of those PHQ values within each region. The middle panel (PRQ graph) shows the population-averaged PRQ for each region over time. The right panels (OHQ graphs) show the population-averaged OHQ for each hospital within a region, also with a "Regional Average" line showing averaged values within each region.

3 RESULTS AND DISCUSSION

3.1 Emergent Phenomena

In this section, we examine the simulation outcomes under the baseline setting, and discuss the *emergent phenomena* that arise from the feedback loop among objective quality (OQ), and perceived quality (PQ). 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*.

3.1.1 Local Dominance

A notable finding is that in certain regions (e.g., SM and YN), a few hospitals exhibit sharp increase of OHQ. In SM, four hospitals rapidly converge to the upper OQ boundary, whereas in YN, a single hospital stabilizes near an OHQ value of 4. We refer to this phenomenon as *Local Dominance*, wherein a small subset of hospitals—*leading hospitals*—attract most of the local patient volume and grow in their OHQ.

This pattern emerges from a positive feedback loop of *scale effect*: as one hospital attracts relatively high volume of patients within a region, it benefits from stronger scale effects, raising its OHQ. In turn, *Quality Recognition* and *Word-of-Mouth* disseminate these quality improvements to patients, further boosting inflow, which in turn leads to an even greater increase in the PHQ of these hospitals. Meanwhile, other local hospitals, lacking sufficient patient volume, see their OHQ stagnate or decline. Consequently, leading hospitals gain a near-monopoly in their region.

From the perspective of the regional 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.

3.1.2 Global Dominance

Local Dominance occurs only in SM and YN, whereas CC, GW, and HN fail to develop any dominant hospitals. In these regions, too many patients are drawn away to other areas, preventing local hospitals from achieving the critical patient volume needed to trigger the loop of positive scale effect. This is particularly due to large metropolitan regions (e.g., SM) attracting a significant share of patients. 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 HN, which initially showed signs of growing a leading hospital. Around time step 250, one HN hospital was experiencing rising OQ. However, the PRQ of SM hospitals grew rapidly, attracting an increasing share of HN patients. Consequently, inflow to HN's leading candidate dropped below the level needed to sustain positive scale effect, causing OHQ to decline. Therefore, even when a region starts to develop *Local Dominance*, it can lose it if another region grow at a faster rate.

We infer that regions with smaller populations or closer proximity to major metropolitan regions are particularly vulnerable to *Global Dominance*. A larger population base increases the chance to maintain the over-threshold inflow needed to develop a leading hospital. Similarly, being farther from metropolitan areas raises travel costs and discourages outmigration, thus alleviating global dominance effects.

3.1.3 Asymmetric Quality Recognition

A further observation is that the trajectories of PHQ and PRQ do not fully mirror the OHQ trends. This is because quality recognition occurs based on hospital utilization by diagnosed patients, which is determined by the choice probability associated with each hospital or region. Hospitals (or regions) with higher existing PQ have higher choice probabilities, thus receiving more patients and exhibit more opportunities for perception updates. Meanwhile, hospitals with lower PQ remain underutilized and stay "off the radar". We refer to this phenomenon as *Asymmetric Quality Recognition*.

Asymmetric Quality Recognition appears at both the PHQ and PRQ levels. At the PHQ level, in the SM region, only four hospitals, precisely matching the leading hospitals, exhibit rising PHQ. If these hospitals gain even a small opportunity early in the simulation to showcase their increasing OHQ, that marginal boost in PHQ leads to higher choice probabilities, in turn creating more chances to reveal their improving OHQ to patients. By contrast, hospitals with lower PHQ continue to have little or no utilization, which means that even if their OHQ decrease, patients have less chance to notice. In other words, weakly perceived hospitals remain "locked in" to their reputation, making it more difficult to overcome negative perceptions through facility upgrades or other quality investments.

At the PRQ level, SM is the only region whose PRQ clearly increases, largely because a substantial share of patients utilizes SM and recognize their quality. Moreover, the trajectory of PRQ in SM is driven by its leading hospitals: patients who select SM often visit one of the high-PHQ hospitals, and their high-OHQ experience raises the perceived quality (PRQ) of the entire region. As a result, SM's PRQ exceed the average OHQ of its hospitals, pulled upward by a few leading hospital—an effect we label as *PRQ traction*. This phenomenon is also based on the entire volume patient inflow to the region, thus operating more strongly in regions with high PRQ. In turn, high-PRQ regions benefit from this *Asymmetric PRQ Traction*, and consequently intensifies *Global dominance* by further enlarging the PRQ gap across regions.

3.1.4 Implications for Patient Concentration

In order to mitigate patient concentration, establishing *Local Dominance* in each region is essential. Regions without a *leading hospital* tend to experience degradation of the whole infrastructure, whereas successful *Local Dominance* can sustain local utilization. However, the emergence of strong leading hospitals in a large metropolitan region often results in *Global Dominance*, draining patient inflows from smaller regions. Meanwhile, *Asymmetric Quality Recognition* disproportionately highlights the success of leading hospitals and regions, making it harder for others to compete. Also, leading hospitals in high-PRQ regions pull upward the PRQ (*PRQ traction*), widening the PRQ gap across regions and accelerating *Global Dominance*.

3.2 Sensitivity Analysis

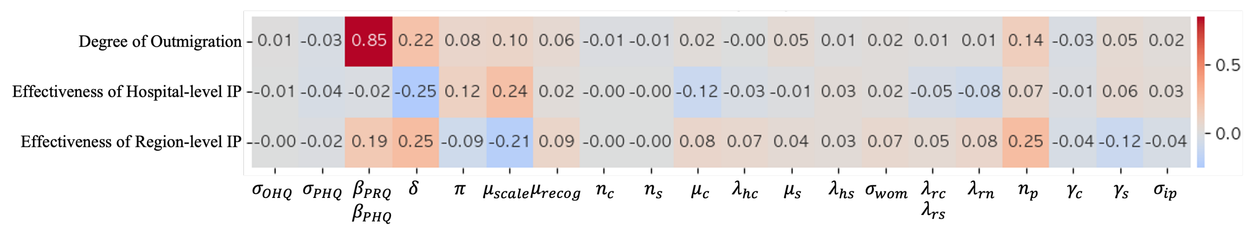


Figure 4: Correlation matrix between simulation parameters and outmigration measures

The heatmap shows the correlation between each simulation parameter (horizontal axis) and three outmigration measures (Degree of Outmigration, Effectiveness of Region-level IP (Information Provision), and Effectiveness of Hospital-level IP)

Building upon the emergent phenomena described above, we conducted a sensitivity analysis to examine how key simulation parameters affect the *degree of outmigration*. Figure 4 shows the correlation matrix between each parameter (horizontal axis) and three outmigration-related measures (vertical axis). The first row (the "Degree of Outmigration" row), shows how each parameter correlates with overall outmigration.

Parameters such as β_{PQ} (β_{PRQ}, β_{PHQ}), δ, μ_{scale}, and n_p stand out as having strong positive correlations with outmigration. Each of these effectively accelerates *Global Dominance* in SM, thereby reducing the chance for *Local Dominance* to form in non-SM regions. A high β_{PQ} means that patients place a greater weight on perceived quality, boosting SM usage initially and impeding the development of *leading hospitals* outside SM. Moreover, it reinforces *Local Dominance* within SM by favoring a few outstanding hospitals that rapidly increase their OHQ, which in turn propels *PRQ traction*. Similarly, a larger δ narrows the distance-related utility gap (in the choice process) between traveling outside one's home region and staying, thereby making outmigration easier and *Local Dominance* harder to achieve. A higher μ_{scale} accelerates the growth of *leading hospitals* in SM once they attract a sufficient number of patients, thereby intensifying *PRQ traction*. Finally, a larger n_p (number of diagnosed patients each step) provides more opportunities for rapid updates to PRQ, further fueling *PRQ traction*, and thus reinforcing *Global Dominance* in SM.

3.3 Information Provision Policy

As discussed previously, the interplay among different quality constructs generates various emergent phenomena, inevitably leading 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:

- **Hospital-level IPP**: Revealing the OHQ of each hospital, thereby influencing PHQ directly.
- **Regional-level IPP**: Revealing the average OHQ of all hospitals within each region, thereby substituting each individual's PRQ.

3.3.1 Experiment Design

At each simulation time step, 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 sensitivity analysis 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 (Default). Details of policy implementation and experiment design can be found in Appendix **??**.

3.3.2 Policy Assessment Results

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.

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 second row of Figure 4, its effectiveness improves with lower δ, higher π, and lower 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), 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 interpretation of the impact of each parameter on policy effectiveness, as shown in Figure 4, can be found in Appendix **??**.

4 CONCLUSION

In this paper, we developed an agent-based simulation framework that captures how objective quality and perceived quality co-evolve through four interaction mechanisms: *Hospital Choice*, *Scale Effect*, *Quality Recognition*, and *Word-of-Mouth*. We observed how this feedback loop can lead to system-level emergent phenomena of *Local Dominance*, *Global Dominance*, and *Asymmetric Quality Recognition*.

Most notably, we identify *Local Dominance*—the emergence of one or a few *leading hospitals* in a region—as a key dynamic that can sustain local healthcare capacity and reduce outmigration. At the same time, *Global Dominance* occurs when an already-strong region (e.g., a major metropolitan area) pulls in excessive patient inflows from other regions, impeding their development of local leading hospitals.

Our simulation results suggest that *encouraging Local Dominance* in non-metropolitan regions is critical for mitigating patient concentration and ensuring equitable access across regions. Rather than attempting to uniformly raise hospital quality, a more effective strategy may be to concentrate resources and patient volume into one or two potential leading hospitals per region. If those hospitals become competitive enough to enter the positive scale-effect feedback loop, patients will have fewer incentives to travel to distant metropolitan areas. In other words, to achieve a nationwide "regionalization" objective, each region may need to focus on a form of *local tiering* that secures sustainability within its own healthcare system.

Furthermore, we examined an *Information Provision Policy* that directly reduces the PQ-OQ gap by disclosing hospitals' OHQ to individuals. We tested two policy implementations (hospital-level versus regional-level) and found that neither option strictly outperforms the other under all settings. Instead, each policy is more effective in different environments: hospital-level disclosure tends to be more beneficial in optimistic settings, where non-SM local dominance is feasible, while regional-level disclosure proves advantageous in pessimistic settings, where global dominance is already strong.

Several avenues exist for further improvement. First, the simulation's fidelity could be enhanced by incorporating more detailed features (e.g., heterogeneity in hospital choice criteria, explicit capacity constraints, sophisticated implementation of scale effects). Second, although our simulation focuses on cancer care in Korea—a context where patient choice is notably influential—future work could extend the model to include multiple disease types or broader healthcare systems, potentially incorporating smaller institutions such as secondary or primary care facilities. Finally, exploring alternative forms of the IPP could offer further perspectives on effective policy choices. Although our current regional-level IPP discloses average OHQ values, it would be worthwhile to consider other regional-level metrics for disclosure.

Despite these limitations, this study provides a valuable framework for examining how perceived and objective quality co-evolve, how feedback loops reinforce regionally skewed utilization patterns, and how targeted information provision can help alleviate patient concentration. We hope that this model-based approach will serve as a foundation for future research and evidence-based policy design in healthcare systems—particularly those, like South Korea's, that emphasize strong patient autonomy in hospital choice.

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A TEMP

Appendices are uploaded in this link...

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