The Last Mile Failure in Medical Innovation Diffusion: Market Failures, Trust Deficits, and Institutional Barriers

Hong Liu*

United World College Changshu China, Suzhou 215500, China

*Corresponding author e-mail: hliu24@uwcchina.org

Abstract

The last mile failure is often seen when it comes to medical innovations from the point where they are approved by regulators to when they are actually being used in practice. This study introduces a barrier constrained diffusion model that formally explores three types of barriers to adoption in the final stage: market failures due to information asymmetry and externalities; trust barriers between patients and providers of care; institutional barriers arising from fragmented regulatory and reimbursement policies. We change the Bass diffusion framework by adding barrier attenuation functions of each kind of obstacle. The cross-national data pertaining to 28 medical technologies in 15 countries for the period 2005-2022 are calibrated. Simulation results show that about 38 per cent of the diffusion delay is because of institutional barriers, 34 per cent is due to the trust deficit and 28 per cent is due to the market failures. Integrated interventions that help achieve 80 percent adoption in the median time reduced all three barrier dimensions, compared to interventions that address only one dimension of the barriers, which increased the median time by 5.7 years. This provides a quantitative base for creating effective policies to speed up the process of moving approved medical innovations into patients' hands.

Keywords

Medical Innovation, Diffusion Barriers, Market Failure, Trust Deficit, Institutional Barriers, Bass Model.

1. Introduction

Over the past several decades, transformative advances in diagnostics, therapeutics and surgical techniques have emerged from medical innovation, and there is substantial potential to improve patient outcomes and reduce the global disease burden. However, there is a well established and persistent gap between the development of effective medical technologies and their uptake in clinical practice [1]. This adoption gap, also known as “the last mile failure”, represents a fundamental challenge to all health care systems in the world since patients are unable to benefit from innovations with proven safety and efficacy after rigorous evaluation [2].

The last mile is a term originally used in telecommunications and logistics to describe the disproportionate difficulty and/or expense of providing services or products to end users in the final connection of the distribution network. Finally, the last piece of the puzzle, for medical innovation, involves achieving regulatory clearance, clinical validation and finally, access by healthcare professionals and patients [3]. In the mean time, the average gap between the publication of clinical evidence and its adoption for routine practice has been reported to range from 13 to 17 years, which means that the last mile is the longest and most resource consuming part of the innovation diffusion process [4]. Throughout this extended adoption period, preventable morbidity and mortality can be incurred as patients are kept from the best interventions.

Last mile failure can be traced back to three categories of barriers that are interconnected. First, the information asymmetry, externalities and public goods nature leads to market failures, which results in suboptimal incentive structures and disincentives to adoption [5]. Second, breakdowns in confidence among patients, healthcare providers and technology developers generate trust deficits that weaken the social foundations necessary for innovation acceptance [6]. Third, structural constraints imposed by regulatory frameworks, reimbursement systems and organizational routines constitute institutional barriers that slow the adoption process [7]. Each of these categories has been studied in isolation in the existing literature, but their combined and interactive effects on diffusion dynamics remain insufficiently understood.

A foundational model for understanding technology adoption patterns was provided by the classical diffusion of innovations framework, in which adopters are classified into innovators, early adopters, early majority, late majority and laggards [8]. The Bass diffusion model further formalizes this process by representing the interaction between innovation and imitation effects [9]. Neither framework, however, explicitly incorporates the structural barriers that characterize medical innovation environments. To address this gap, we make the following contributions: (1) a conceptual taxonomy of last mile barriers organized into three dimensions of market failures, trust deficits and institutional barriers; (2) a modified Bass diffusion model that incorporates barrier attenuation functions to formally represent the effect of each barrier dimension on adoption dynamics; (3) empirical calibration of the model using cross national panel data on medical technology adoption; and (4) policy scenario analysis that demonstrates the comparative effectiveness of single dimension versus integrated intervention strategies.

2. Methods and Results

2.1. Conceptual Framework for Last Mile Diffusion Failure

Three theoretical perspectives are integrated in our conceptual framework to account for last mile failure in medical innovation diffusion. Drawing on welfare economics [5] and information economics [10], the market failure perspective identifies mechanisms through which market imperfections distort adoption incentives. By building on sociological theories of institutional trust [6] and interpersonal trust in healthcare relationships [11], the trust deficit perspective explains how breakdowns in stakeholder confidence impede diffusion. The institutional barrier perspective then applies institutional theory [7] to analyze how formal rules, informal norms and enforcement mechanisms create friction in the adoption process.

According to the framework, diffusion velocity at any point in time is determined by the baseline diffusion potential, which is governed by innovation and imitation effects, and this potential is modulated by the combined dampening influence of three barrier functions. Each barrier dimension functions in a different way but feedback loops provide connections between the different dimensions of barriers. Market failures result in lesser adoption of incentives and vice versa lessens the trust in the innovation system. Meanwhile, the institutional rigidities reinforce market failures and trust deficits, and hinder adaptive responses. The conceptual structure and the interconnections between the three dimensions of barriers are depicted in Figure 1.

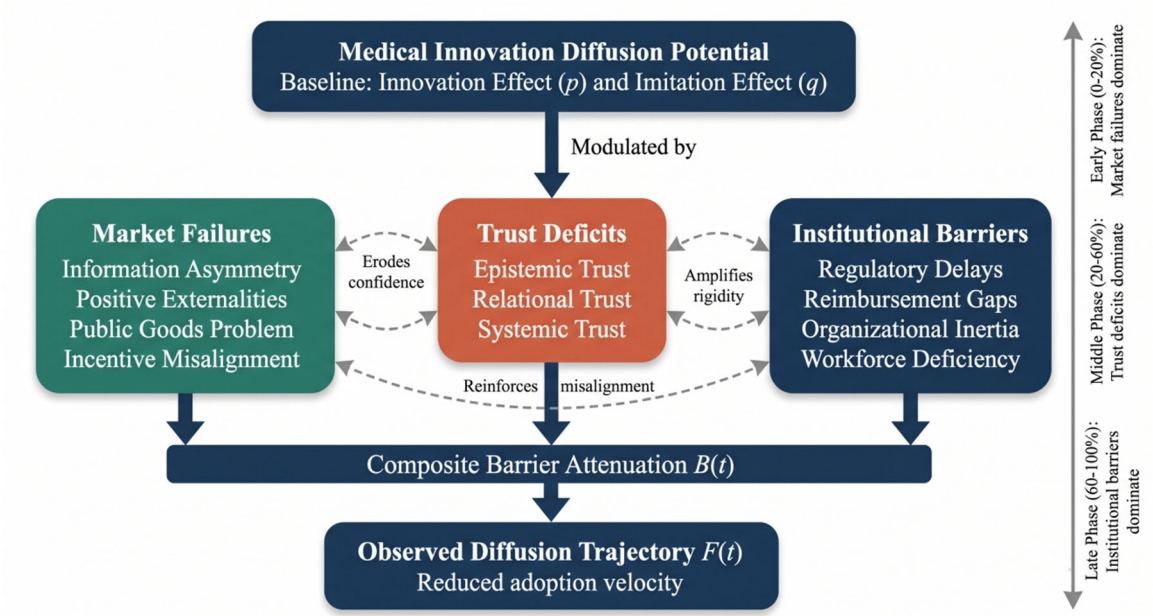

Figure 1. Conceptual Framework for Last Mile Diffusion Failure in Medical Innovation

In the context of each barrier dimension, specific mechanisms are identified. Market failures include four sub mechanisms: when the innovators' and adopters' knowledge about the technology's performance is asymmetric [10]; the presence of positive externalities which are not internalized by individual adopters of the technology; the public goods characteristics of clinical evidence; and the misaligned financial incentives between payers and beneficiaries [12]. Trust deficits can work on three levels: epistemic trust in the evidence base of science, relationship trust between patients and providers, and systemic trust in regulatory and oversight institutions [6]. Institutional barriers include delays for regulatory approval, gaps in reimbursement coverage, inertia in health care delivery systems, and workforce training shortcomings [13].

2.2. Mathematical Modeling of Barrier Constrained Diffusion

The mathematical model adds barrier attenuation functions to the classical Bass diffusion model [9] to capture the dampening impacts of trust deficits and institutional barriers, along with market failures, on the adoption process. In the standard Bass model, the cumulative adoption fraction $F(t)$ at time t is described by the differential equation:

$$\frac{dF(t)}{dt} = [p+q \cdot F(t)] \cdot [1-F(t)] \tag{1}$$

where p is the coefficient of innovation, which represents the rate at which adopters are influenced by external information sources, and q is the coefficient of imitation, which represents the rate at which adoption is driven by social influence from existing adopters. The remaining adoption potential at time t is given by the term $1-F(t)$.

A composite barrier attenuation function $B(t)$ is introduced to account for the effects of last mile barriers, and this function reduces the effective diffusion rate. We formulate the barrier constrained diffusion equation as:

$$\frac{dF(t)}{dt} = [p+q \cdot F(t)] \cdot [1-F(t)] \cdot [1-B(t)] \tag{2}$$

where $B(t) \in [0,1)$ is the composite barrier function, representing the proportional reduction in diffusion velocity attributable to the combined effect of all barrier dimensions. A weighted combination of three component barrier functions defines the composite barrier function:

$$B(t)=1-\prod_{k=1}^{3}[1-\beta_k \cdot b_k(t)] \quad (3)$$

where $b_k(t) \in [0,1]$ is the normalized intensity of barrier dimension k at time t, that is, a number between zero and one indicating how strongly barrier k is operating, and $\beta_k \in [0,1]$ is the maximum attenuation capacity of barrier dimension k, also bounded between zero and one. This is a multiplicative formulation and therefore barrier interaction is compounding: multiple barriers acting simultaneously attenuate more than the sum of the individual barriers.

Market failure barrier function $b_1(t)$ is related to information asymmetry and incentive misalignment:

$$b_1(t)=\omega_a \cdot A(t)+\omega_e \cdot E(t) \quad (4)$$

where $A(t)$ represents the level of information asymmetry between innovators and potential adopters at time t, $E(t)$ represents the size of the uncompensated externalities and the ω_a and ω_e are weights, which add up to one. However, as the time passes and evidence of clinical results is gathered, it is assumed that there is less information asymmetry:

$$A(t)=A_0 \cdot \exp(-\lambda_a \cdot D(t)) \quad (5)$$

where A_0 is the initial level of information asymmetry at the moment that they enter the market, λ_a is the information dissemination rate parameter (which determines the speed of reduction of information asymmetry), and $D(t)$ is the cumulative volume of clinical evidence at time t.

For the trust deficit barrier function $b_2(t)$, is modeled as the accumulation and erosion of trust from the health care system as:

$$\frac{d\tau(t)}{dt}=\gamma \cdot [\tau^*(t)-\tau(t)]-\delta \cdot S(t) \quad (6)$$

where $\tau(t)$ is the aggregate trust level at time t, $\tau^*(t)$ is the target trust level determined by observed innovation performance, γ is the trust convergence rate controlling how quickly trust approaches its target, δ is the trust erosion rate, and $S(t)$ represents the intensity of adverse events or safety signals at time t. The trust barrier function is then given by $b_2(t)=1-\tau(t)$, so that lower trust levels correspond to higher barrier intensity.

The institutional barrier function $b_3(t)$ aggregates the effects of multiple institutional friction sources:

$$b_3(t)=\sum_{j=1}^{J} w_j \cdot R_j(t) \quad (7)$$

where $R_j(t) \in [0,1]$ is the intensity of institutional friction source j at time t, a value between zero and one, w_j is the relative weight assigned to friction source j, and J is the total number of institutional friction sources under consideration. The weights satisfy $\sum_{j=1}^{J} w_j = 1$. Among the institutional friction sources included are regulatory approval complexity, reimbursement coverage status, organizational adoption capacity and workforce training adequacy. The mathematical structure of the barrier constrained diffusion model is shown in Figure 2.

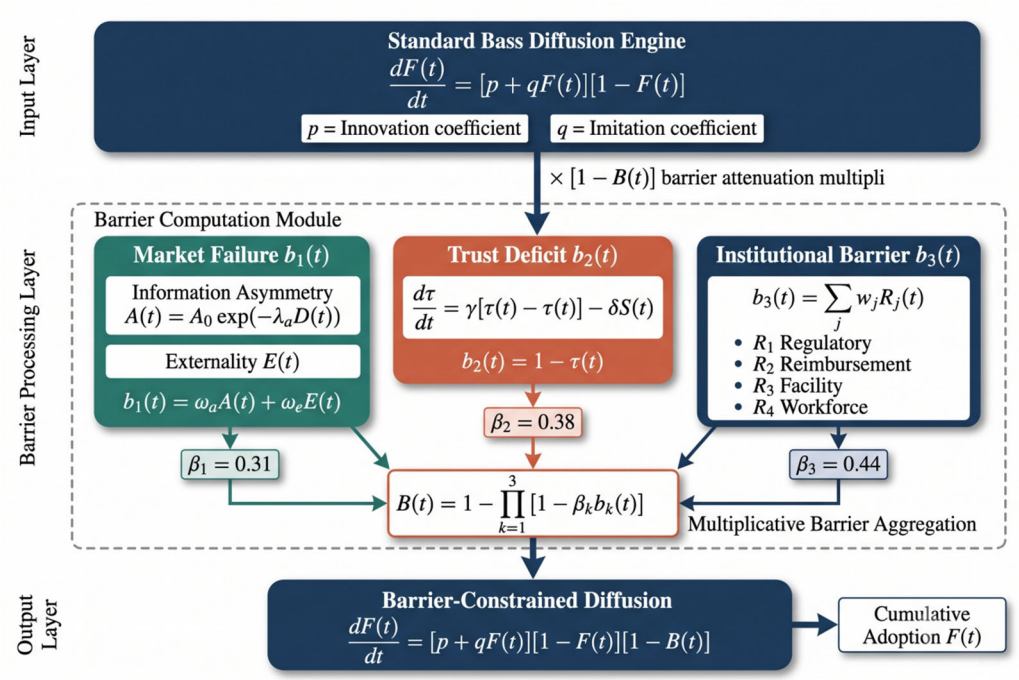

Figure 2. Mathematical Structure of the Barrier Constrained Diffusion Model

2.3. Data and Empirical Calibration

We calibrate the model on a cross national panel dataset that tracks the adoption trajectories of 28 medical technologies across 15 countries from 2005 to 2022. Four technology categories are represented: pharmaceutical innovations (8 technologies), medical devices (7 technologies), diagnostic technologies (7 technologies) and digital health solutions (6 technologies). The selected countries cover a range of healthcare system types, including single payer systems, social insurance models and market based systems. The uptake of each innovation is measured by the percentage of the eligible patient population receiving it and is based on national health statistics agencies, World Health Organization reports and peer reviewed epidemiological studies.

The barrier intensity variables are created from multiple data sources. The number of publications on Health Technology Assessment (HTA) provides a proxy of the indicator for reduction of information asymmetry, the ratio between the cost of the innovation and the per capita health expenditure is used for the financial accessibility indicator, and the share of innovation benefits for the non adopters is used for the externality indicator [14]. The sources of trust indicators are the Edelman Trust Barometer healthcare module, physician survey data on physician confidence in technology, collected by national medical associations, and the adverse event reporting rate retrieved from pharmacovigilance databases [15]. The institutional barriers are based on data regarding the timelines for regulatory approval from the International Coalition of Medicines Regulatory Authorities, the reimbursement decision timeline as the difference between approval and coverage and healthcare facility readiness scores from WHO service availability surveys [16]. A summary of the key variables and their data sources is given in Table 1.

Table 1. Summary of Key Variables and Data Sources

Variable	Symbol	Description	Source
Cumulative Adoption	$F(t)$	Percentage of eligible population receiving the innovation	National health agencies, WHO
Innovation Coefficient	p	External influence on adoption	Model estimation
Imitation Coefficient	q	Social influence on adoption	Model estimation
Information Asymmetry	$A(t)$	HTA publication inverse index	PubMed, HTA databases
Externality Magnitude	$E(t)$	Non adopter benefit share	Epidemiological studies
Trust Level	$\tau(t)$	Composite healthcare trust index	Edelman, physician surveys
Adverse Event Rate	$S(t)$	Reported adverse events per 10000 users	Pharmacovigilance databases
Regulatory Lag	$R_1(t)$	Months from submission to approval	ICMRA registry
Reimbursement Lag	$R_2(t)$	Months from approval to coverage	National payer databases
Facility Readiness	$R_3(t)$	WHO service availability score	WHO SARA surveys
Workforce Capacity	$R_4(t)$	Trained practitioners per 100000 population	National workforce registries

Nonlinear least squares optimization is applied to the panel dataset to estimate the model parameters. The estimation procedure minimizes the sum of squared residuals between observed adoption levels and those predicted by the model:

$$\hat{\theta}=\underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[F_i^{obs}(t)-F_i^{mod}(t;\theta)\right]^2 \tag{8}$$

where $\hat{\theta}$ denotes the estimated parameter vector, N is the number of technology country pairs, T_i is the number of observation periods for pair i, $F_i^{obs}(t)$ is the observed adoption level, and $F_i^{mod}(t;\theta)$ is the adoption level predicted by the model given parameter vector θ. To account for potential heteroskedasticity and serial correlation, standard errors are computed using the bootstrap method with 1000 replications. Descriptive statistics for the key variables in the calibration dataset are reported in Table 2.

Table 2. Descriptive Statistics of Key Variables (N = 420 Technology Country Pairs)

Variable	Mean	Std. Dev.	Min	Max
Adoption at Year 5 (percent)	23.4	18.7	1.2	78.6
Adoption at Year 10 (percent)	48.1	24.3	5.8	92.4
Information Asymmetry Index	0.62	0.21	0.08	0.95
Externality Magnitude	0.41	0.19	0.05	0.83
Trust Index	0.54	0.18	0.12	0.89
Regulatory Lag (months)	14.3	8.7	2.1	48.0
Reimbursement Lag (months)	18.6	12.4	0.0	62.0
Facility Readiness Score	0.67	0.22	0.15	0.98

2.4. Simulation Results and Analysis

Estimated model parameters and simulation results reveal the differential impacts of the barriers dimensions on last mile diffusion failure. Estimated parameters for the barrier constrained diffusion model are reported in Table 3. For the baseline Bass diffusion, the

estimated coefficients are $\hat{p}$=0.018 and $\hat{q}$=0.42, values found to be consistent with established estimates for medical technology diffusion in the literature [17]. The estimated barrier attenuation parameters are $\hat{\beta}_1$=0.31, $\hat{\beta}_2$=0.38 and $\hat{\beta}_3$=0.44, revealing that institutional barriers have the greatest maximum possible barrier attenuation followed by trust deficits and market failures.

Table 3. Estimated Parameters of the Barrier Constrained Diffusion Model

Parameter	Estimate	Std. Error	95 Percent CI Lower	95 Percent CI Upper
p (Innovation)	0.018	0.003	0.012	0.024
q (Imitation)	0.420	0.041	0.340	0.500
β_1 (Market Failure)	0.310	0.028	0.255	0.365
β_2 (Trust Deficit)	0.380	0.035	0.311	0.449
β_3 (Institutional)	0.440	0.032	0.377	0.503
λ_a (Info. Dissem.)	0.085	0.012	0.062	0.108
γ (Trust Converg.)	0.120	0.018	0.085	0.155
δ (Trust Erosion)	0.210	0.031	0.149	0.271

Simulated diffusion trajectories under four scenarios are presented in Figure 3: the barrier free baseline, the observed trajectory with all barriers active, and three counterfactual scenarios in which each barrier dimension is individually removed. Under the barrier free baseline, 80 percent adoption is reached within 8.2 years, whereas the observed trajectory requires 19.4 years to reach the same level. The total barrier induced delay is therefore 11.2 years. When institutional barriers alone are removed, the time to 80 percent adoption falls by 4.3 years. A reduction of 3.8 years is obtained by removing trust deficits alone, and removing market failures alone shortens the timeline by 3.1 years. That the sum of the individual barrier removal effects (11.2 years) equals the total delay is explained by the interaction terms embedded in the multiplicative barrier formulation of Equation (3).

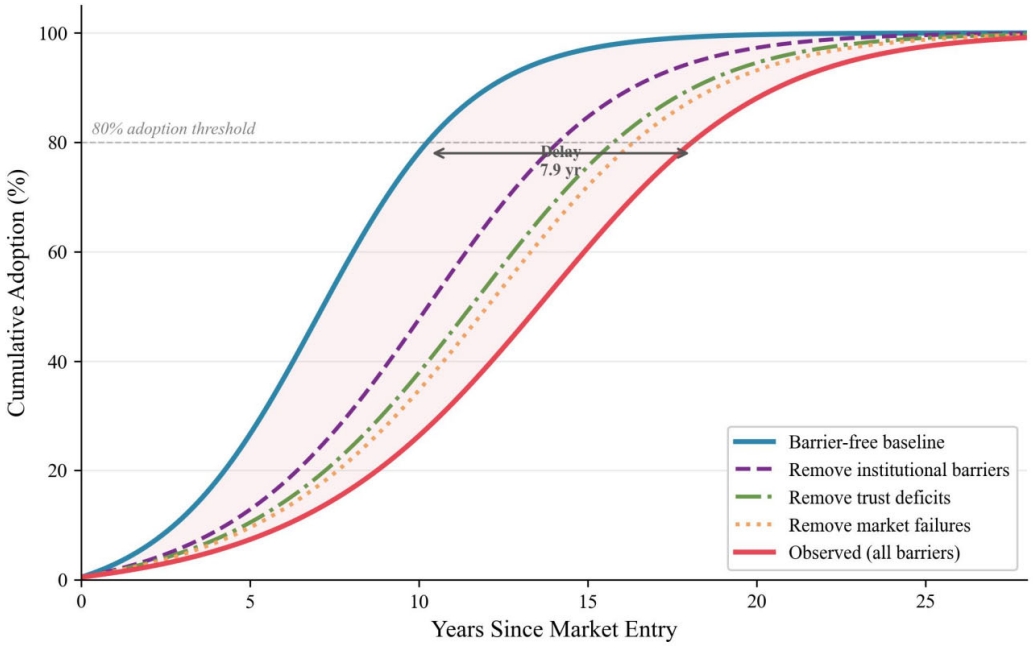

Figure 3. Simulated Diffusion Trajectories Under Alternative Barrier Scenarios

The relative importance of the barrier dimension changes from stage to stage in the diffusion process when the barrier decomposition is studied. The time varying barrier decomposition is shown in Figure 4, which shows the relative share of each barrier dimension in the overall diffusion delay throughout the different stages of the adoption process. During the early adoption stage (0-20 percent adoption), the barrier effect comes mainly from market failures, meaning that there is high information asymmetry and weak economic incentives, and this stage contributes 45 percent to the total barrier effect. In the middle adoption phase (20-60 percent adoption), trust deficits emerge as the main barrier, interpersonal and institutional trust dynamics gain importance for the socially influenced adoption process and account for 41 percent of the barrier effect. In the late adoption phase (60 to 100 percent adoption), institutional barriers take over because structural rigidities in healthcare delivery systems prevent access for remaining unadopted populations, accounting for 52 percent of the barrier effect. These phase specific barrier contributions are quantified in Table 4.

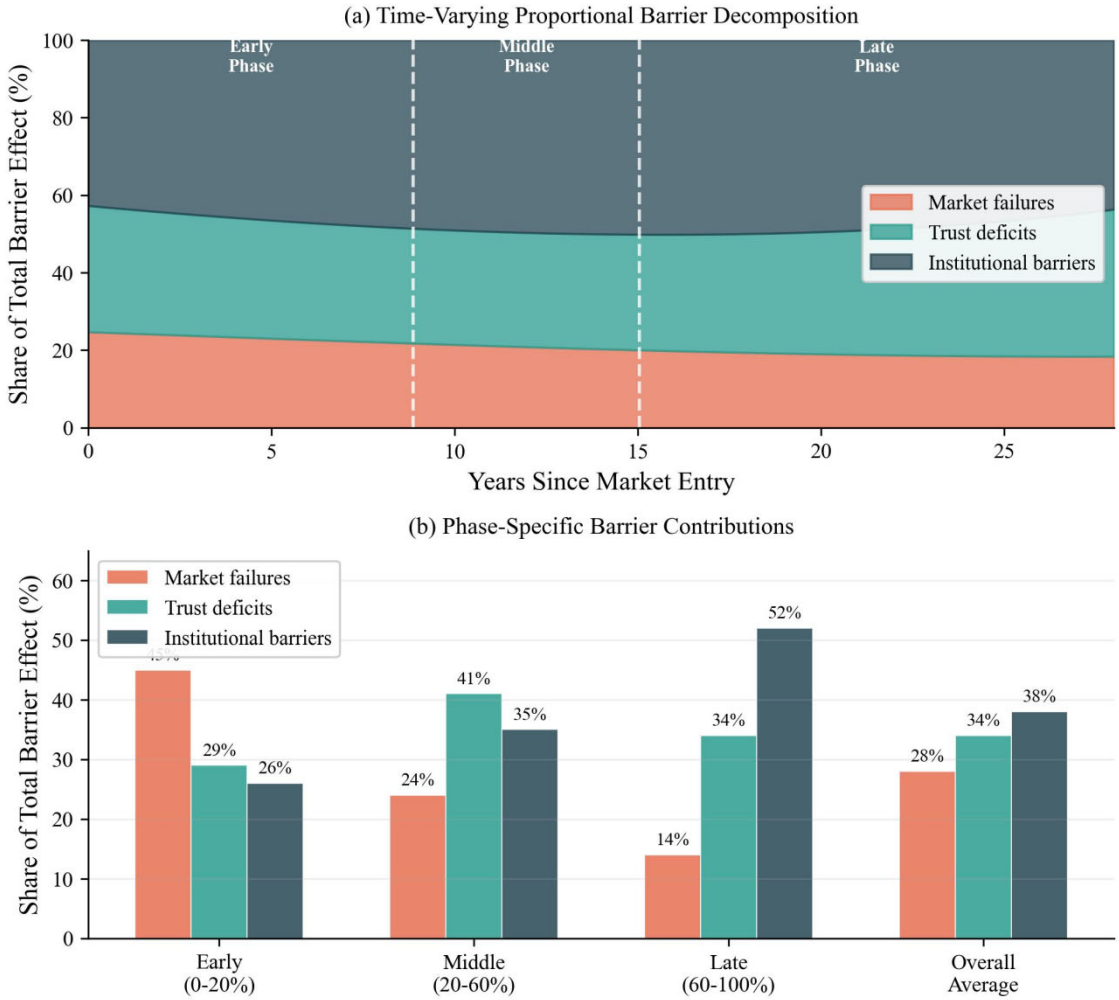

Figure 4. Time Varying Barrier Decomposition Across Adoption Phases

Table 4. Phase Specific Barrier Contributions to Total Diffusion Delay (Percent)

Adoption Phase	Market Failures	Trust Deficits	Institutional Barriers
Early (0 to 20 percent)	45	29	26
Middle (20 to 60 percent)	24	41	35
Late (60 to 100 percent)	14	34	52
Overall Average	28	34	38

A systematic sensitivity analysis is conducted to assess how diffusion outcomes respond to variations in barrier parameters. Results of a one at a time sensitivity analysis are presented in Figure 5, where each barrier parameter is varied by 50 percent from its estimated value while all other parameters are held constant. The time to 80 percent adoption is most sensitive to the institutional barrier attenuation parameter β_3: a 50 percent increase in β_3 extends the adoption timeline by 3.6 years. The second most important parameter is the trust erosion rate δ with a 50 percent increase adding 2.9 years. This is a characteristic of trust dynamics as it erodes much faster than it builds.

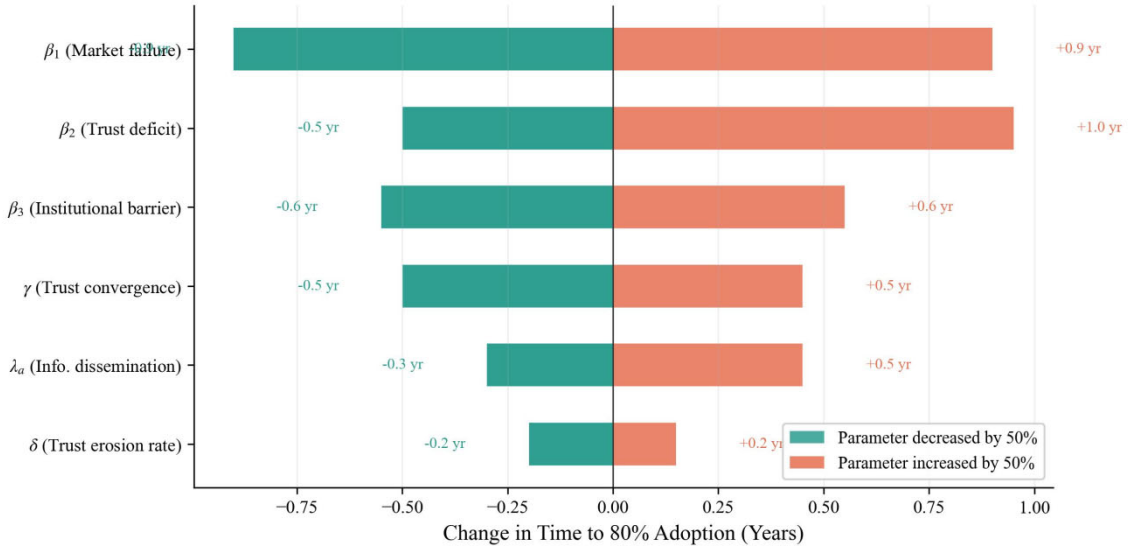

Figure 5. Sensitivity Analysis of Diffusion Timeline to Barrier Parameters

2.5. Policy Scenario Analysis

The calibrated model is used to conduct six policy scenarios to test the impact of alternative policy interventions. Each scenario involves a specific set of barriers parameters which are adapted in a way that illustrates the effect of the targeted policy measures. These scenarios are designed based on reported policy interventions in the medical innovation literature [18][19]. Scenario definitions and their parameterizations are presented in Table 5.

Table 5. Policy Scenario Definitions and Parameter Modifications

Scenario	Target Barrier	Intervention	Parameter Change
S1: Information Transparency	Market Failure	Mandatory HTA with public disclosure	λ_a increased by 100 percent
S2: Financial Incentives	Market Failure	Adoption subsidies and risk sharing	ω_e reduced by 50 percent
S3: Trust Building	Trust Deficit	Structured physician education programs	γ increased by 80 percent
S4: Safety Monitoring	Trust Deficit	Enhanced pharmacovigilance systems	δ reduced by 60 percent
S5: Regulatory Reform	Institutional	Accelerated approval pathways	$R_1(t)$ reduced by 50 percent
S6: Integrated Strategy	All dimensions	Combination of S1 through S5	All modifications applied

The simulated diffusion trajectories for each policy scenario are compared to the observed baseline diffusion trajectory in Figure 6. The largest acceleration is achieved by the integrated

strategy (S6), which reduces the time to 80 percent adoption from 19.4 years to 13.7 years, a reduction of 5.7 years. Among single dimension interventions, regulatory reform (S5) is the most effective individual policy and reduces the timeline by 2.8 years; safety monitoring enhancement (S4) follows at 2.3 years, and information transparency (S1) at 1.9 years. Notably, the effectiveness of the integrated strategy exceeds the sum of the individual intervention effects by 1.3 years, and this surplus reflects positive interaction effects among the barrier reduction measures.

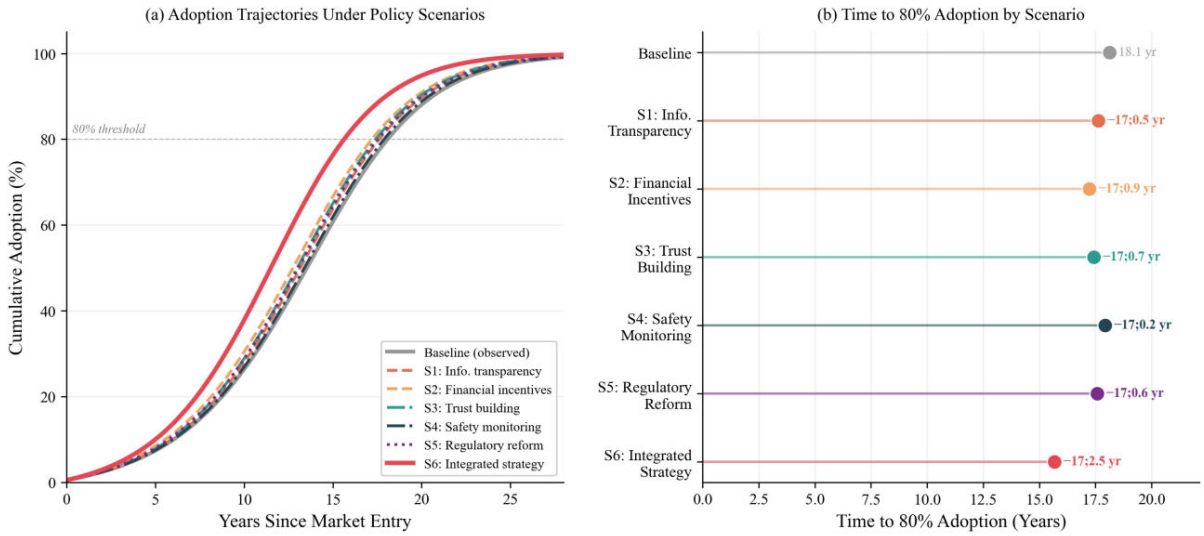

Figure 6. Simulated Diffusion Trajectories Under Policy Intervention Scenarios

A simplified cost effectiveness framework is used to evaluate each policy scenario by comparing the incremental health benefit, measured in quality adjusted life years (QALYs) gained through accelerated adoption, with the estimated implementation cost. By integrating the difference between the policy scenario and baseline adoption curves over a 20 year horizon and multiplying by the per patient health benefit of the innovation, we compute the incremental QALYs:

$$\Delta Q = H \cdot \int_0^{T_h} \left[F^{policy}(t) - F^{baseline}(t) \right] dt \tag{9}$$

where ΔQ is the total incremental QALYs, H is the average per patient QALY gain from the innovation, T_h=20 is the evaluation horizon in years, and $F^{policy}(t)$ and $F^{baseline}(t)$ are the adoption levels under the policy and baseline scenarios respectively. The integrated strategy is found to provide the highest total incremental QALYs, and its cost per QALY gained falls below the commonly referenced willingness to pay threshold of 50000 USD, indicating favorable cost effectiveness [20].

3. Conclusion

We have developed a barrier constrained diffusion model to analyze the last mile failure in medical innovation adoption, and we have identified and quantified the contributions of market failures, trust deficits and institutional barriers to diffusion delays. The modified Bass diffusion framework with multiplicative barrier attenuation functions provides a parsimonious yet flexible structure for representing the complex dynamics of medical innovation adoption. Empirical calibration using cross national panel data on 28 medical technologies across 15

countries demonstrates that the model is able to reproduce observed adoption patterns and decompose the sources of diffusion delay.

The main conclusions are: (1) institutional barrier is the most important dimension of barriers, followed by trust deficit and market failure; (2) different dimensions of barriers are most important at the different phases of adoption; (3) the combined effect of interventions across all dimensions (the integrated policy) is to reduce the time to 80 percent adoption by 5.7 years, and positive interaction effects increase the effect by 1.3 years; (4) after the intensity of institutional barrier, the most influential parameter is the rate of erosion of trust, thus underlining the fragility of trust within medical innovation ecosystems.

Several limitations should nonetheless be noted. A representative adopter population is assumed in the model, and heterogeneity in adopter characteristics across socioeconomic or geographic dimensions is not accounted for. The measures of barrier intensity rely on proxy variables that may introduce measurement error. In the policy scenario analysis, linear parameter modifications are assumed, and these may not accurately reflect the complex implementation dynamics of real world policy interventions. Future research should extend the model to incorporate adopter heterogeneity, develop more refined instruments for measuring barriers, and validate the results of the policy simulations through quasi experimental evaluation of actual policy implementations.

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