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Review

Bridging the Knowledge Void: A Synthetic Near-Empty Review of Intelligent Evolutionary Games Employment in Healthcare

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Abstract

Background: The convergence of Evolutionary Game Theory (EGT) and Artificial Intelligence (AI) has established the field of Intelligent Evolutionary Games (IEG). While IEG applications have flourished in general systems and social sciences, their operationalization within healthcare (IEG Health) remains significantly underdeveloped. This study identifies a "knowledge void" in the literature, where the bottleneck is not a lack of clinical data but a scarcity of frameworks that integrate intelligent strategic modeling into clinical practice. **Methods:** We employ the Synthetic Near-Empty Review (SNER) framework, utilizing Synthetic Knowledge Synthesis (SKS) and bibliometric triangulation via VOSviewer. Three distinct corpora—IEG Health (), EG Health (), and IEG All ()—were harvested from Scopus and mapped to identify thematic clusters and translation pathways. **Results:** The analysis reveals that IEG Health is a nascent domain currently focused on service regulation in elderly care and chronic disease management. We demonstrate a "Translation Framework" to bridge the research void, mapping concepts like Social Trust and Reputation Management from the broader IEG literature into clinical-specific models, such as Doctor-AI Adoption and Adaptive Coordination Games. **Conclusions:** By shifting from static replicator dynamics to Adaptive Learning Strategies (e.g., MARL and Bayesian updating), IEG Health can address critical challenges like algorithm aversion and clinical deskilling. This study provides a structured foundation for future research to transition from theoretical modeling to AI-augmented clinical decision-making.

Keywords: evolutionary game theory; intelligent evolutionary games; multi-agent reinforcement learning; replicator dynamics; synthetic near-empty review; algorithm aversion

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1. Introduction

The synthesis of Evolutionary Game Theory (EGT) [1] and Artificial Intelligence (AI) [2] has given rise to a potent interdisciplinary framework: Intelligent Evolutionary Games (IEG) [3,4] . While classical EGT focuses on the dynamics of strategy propagation within populations based on fitness and natural selection, the integration of "intelligence"—ranging from reinforcement learning [5], cognitive modelling [6], co-evolutionary algorithms [7] or Multi-Agent Reinforcement Learning [6] introduces a more nuanced dimension to strategic interaction [8].

However, a critical research gap persists within the healthcare sector: the primary bottleneck is not a lack of raw biological or clinical data, but a profound scarcity of peer-reviewed publications that operationalize IEG frameworks in real-world healthcare contexts. This creates a "near-empty" research space that hinders the transition from theoretical modelling to clinical practice. To navigate this, the Synthetic Near Empty Review (SNER) framework [9] offers a transformative solution. By utilizing a triangulation of bibliometric mapping and synthetic thematic analysis, the SNER

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framework allows researchers to extract knowledge from emerging or sparse literature landscapes. This approach addresses the problem of reviews being "as empty as possible" by generating a structured, evidence-based foundation where traditional systematic reviews fail. By applying the SNER framework, researchers can identify underlying strategic paradigms from fields characterized by the proven efficacy of IEGs and EGT. This approach serves to bridge critical void in the IED employment in healthcare through the generation of systemic, AI-augmented synthesis.

2. Methodology

The SNER framework is based on Synthetic Knowledge Synthesis (SKS) [10,11]. SKS exhibits several advantages over traditional review frameworks. It reduces the time and resources required to synthesize articles, thus enabling the analysis of "whole corpora" of publications (all publications from fields of interest) rather than being limited to small, manually selected samples. In this manner sampling bias is avoided. Additionally, the use of bibliometric landscapes makes it easier to visualize, identify and analyse associations between different author keywords, topics or others units of interest. Furthermore triangulation" (combining bibliometrics and content analysis of publications metadata) supports a holistic understanding of the research presented in corpora being synthetised.

The methodological framework based on for this study is illustrated in Figure 1. Initially, SKS is employed to map the research landscapes of IEG Health (publications presenting the use of IEG in healthcare), EG Health (publications presenting the use of EGT in healthcare), and IEG All (publications presenting the use of IEG in general), facilitating the identification of prominent themes within each respective field. Subsequently, a comparative analysis of IEG Health themes against those of IEG All and EG Health is conducted to distinguish specific knowledge areas and themes suitable for translation into the IEG Health void. Each identified theme is then systematically decomposed into its constituent health domains and AI technologies, thereby delineating potential implementations of IEG within the healthcare sector.

Figure 1. The framework of the SNER methodology used in the IEG Health study.

The three corpora presented above were harvested from the Scopus bibliographic database on 16th of February, using the following search strings:

- **IEG Health:** TITLE-ABS-KEY("evolutionary game*" and ("intelligen*" OR "machine learning" OR "deep learning" OR "intelligent system" OR "support vector machine" OR ("decision tree" AND (induction OR heuristic)) OR "random forest" OR "Markov decision process" OR "hidden

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Markov model" OR "fuzzy logic" OR "k-nearest neighbours" OR KNN OR "support vector machine*" or SVM OR "naive Bayes" OR "Bayesian learning" OR "artificial neural network" OR "convolutional neural network" OR "recurrent neural network" OR "generative adversarial network" OR "deep belief network" OR "perceptron" OR {natural language processing} OR {natural language understanding} OR {general language model})) AND (LIMIT-TO (SUBJAREA,"MEDI") OR LIMIT-TO (SUBJAREA,"HEAL"))

- **EG Health:** TITLE-ABS-KEY("evolutionary game*") AND (LIMIT-TO (SUBJAREA,"MEDI") OR LIMIT-TO (SUBJAREA,"HEAL"))
- **IEG All:** TITLE-ABS-KEY("evolutionary game*" and ("intelligen*" OR "machine learning" OR "deep learning" OR "intelligent system" OR "support vector machine" OR ("decision tree" AND (induction OR heuristic)) OR "random forest" OR "Markov decision process" OR "hidden Markov model" OR "fuzzy logic" OR "k-nearest neighbours" OR KNN OR "support vector machine*" or SVM OR "naive Bayes" OR "Bayesian learning" OR "artificial neural network" OR "convolutional neural network" OR "recurrent neural network" OR "generative adversarial network" OR "deep belief network" OR "perceptron" OR {natural language processing} OR {natural language understanding} OR {general language model}))

Bibliometric mapping was conducted using VOSviewer version 1.6.20 [12] to visualize the structural and thematic relationships within the identified literature. The resultant research landscapes, which illustrate the conceptual clusters and evolutionary trajectories of the field, are presented in Figures 2 through 4. Complementing this visualization, the findings derived from the systematic content analysis of these landscapes are synthesized in Table 1. This table delineates the corpus across four critical dimensions: (i) Overarching research themes, (ii) Specific healthcare domains, (iii) Evolutionary game strategies, and (iv) Integrated AI algorithms and paradigms.

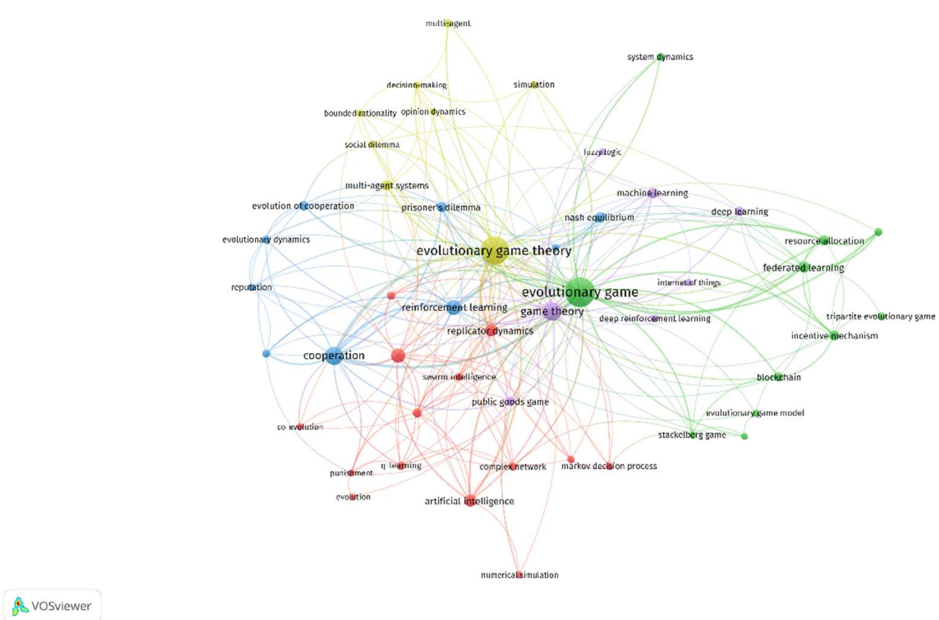

Figure 2. The research landscape induced from the IEG All corpora of publications.

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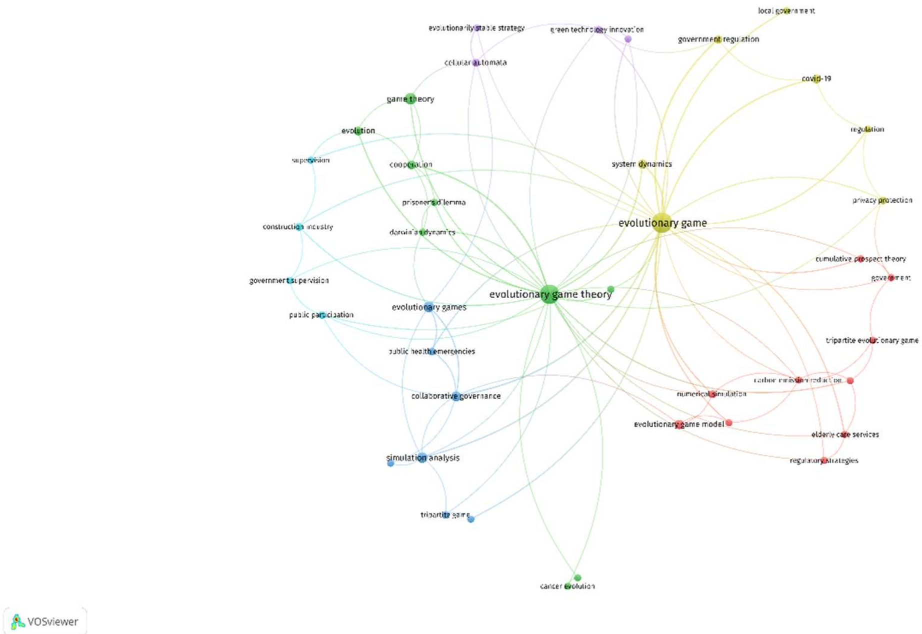

Figure 3. The research landscape induced from the EG Health corpora of publications.

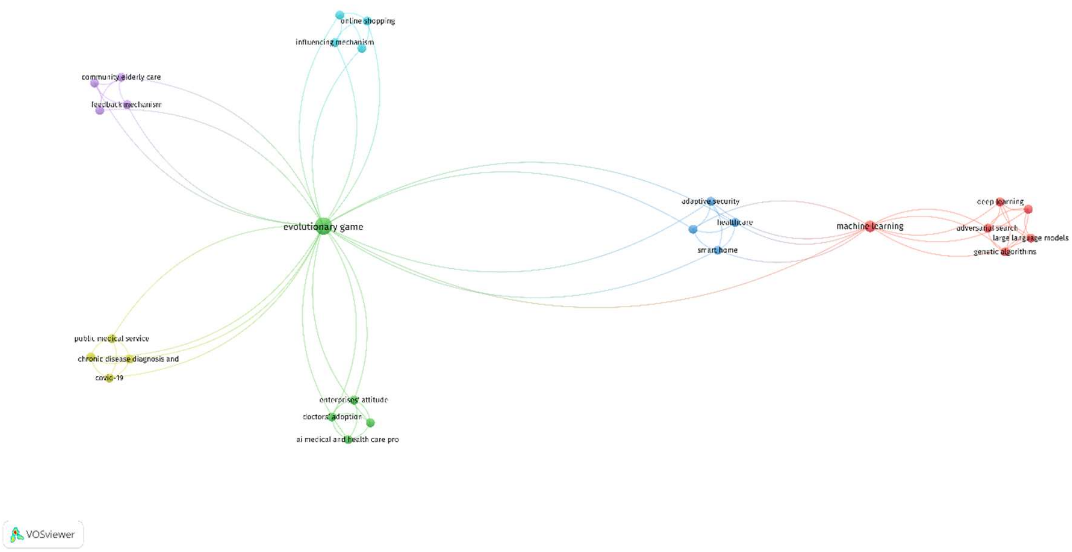

Figure 4. The research landscape induced from the IEG Health corpora of publications.

Table 1. The results of the thematic analysis.

	IEG All	EG Health	IEG Health
Overreaching research themes	Reputation management	Public participation in governmental supervision	Service regulation in community elderly care
	Public good management	Collaborative governance in public health emergencies	Public medical services for chronic disease diagnosing and treatment

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	Solving social dilemmas	Green technology innovation	Privacy protection
	Trust evaluation	Government regulation and privacy protection in health crises	Doctors adoption to AI based medicine
	Decision making	Regulation strategies in elderly care ser vices	Adaptive security of healthcare in smart homes
	Task allocation	Carbon emission reduction	
	Smart supply chains	Drug resistance and cancer evolution	
	Resource allocation		
	Multi-objective optimization		
	Value co-creation		
	Intelligent construction		
	Population dynamics		
	Auction		
	Social networking		
Specific healthcare domains		Privacy protection	Smart home
		Green technologies	AI based medicine
		Cancer evolution	Chronic diseases
		Drug resistance Food and product safety (MAH – Marketing Authorization Holder mechanism)	
		Immunotherapy	
		Disease transmission	
		Angiogenesis	
Evolutionary game strategies	All from EG Health	Cellular automata	
	Collective intelligence	Prisoners' dilemma	
	Replicator dynamics	Darwinian dynamics	
	Nash equilibrium	Cumulative prospect theory	
	Stackelberg game	Hawk-dove game	
	Co-operation dynamics	Reciprocal altruism	
	Snowdrift game	Agent based technologies	
Integrated AI algorithms and domains	All from IEG Health		Deep learning
	Swarm intelligence		Large language models
	Neural network		Genetic algorithms
	Federated learning		Adversarial search
	Edge intelligence		
	Deep reinforcement learning		
	Multi – agent reinforcement learning		
	Q-learning		

3. Results and Discussion

The search result16 publications presenting the use of IEG in health, 335 publications presenting the employment of EG in health and 1124 presenting the use of IEG in general. The research landscapes induced by VOSViewer are shown in Figures 2 to 4, and the result of thematic analysis in Table 1. The themes across the three corpora of publications reflect a transition from broad social management to specialized medical regulation:

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- IEG All: Focuses on high-level systemic issues such as reputation management [12], public good management [13], and solving social dilemmas [14]. It also touches on infrastructure and logistics like smart supply chains [15] and intelligent construction [15].
- EG Health: Shifts the focus toward governance and public safety, emphasizing collaborative governance in emergencies [16], green technology innovation [17], and governmental supervision [18].
- IEG Health: Narrowly targets the intersection of technology and medicine, specifically service regulation in elderly care [19], AI adoption by doctors, and smart homes [20].

The Table 1. highlights where these game-theoretic models are applied within the healthcare field as shown bellow:

- EG Health Applications: Covers biological and systemic health issues including cancer evolution, drug resistance, immunotherapy, and disease transmission [21–24]. It also addresses industrial health factors like food and product safety [25].
- IEG Health Applications: Focuses on technology-driven healthcare delivery, such as smart homes, AI-based medicine, and chronic disease management [26,27].
- General IEG/EG Strategies: Utilize classic models like the Prisoner's Dilemma, Snowdrift game, and Hawk-dove game [28–30].
- Dynamics and Theory: Both domains rely on Replicator dynamics, Nash equilibrium, and Stackelberg games to understand how cooperation or competition evolves over time [31–33].
- Advanced Modelling: Includes Cellular automata, Cumulative prospect theory, and Agent-based technologies to simulate more complex, non-linear human or other health agents behaviours [33,34].
- Broad Intelligence (IEG All): Leverages a wide array of AI techniques, including Swarm intelligence, Federated learning, and Edge intelligence. It also uses Multi-agent reinforcement learning and Q-learning for decision-making [35–39].
- Healthcare Intelligence (IEG Health): Specifically highlights the use of Deep learning, Large Language Models (LLMs), Genetic algorithms, and Adversarial search to solve health-specific problems [39,40].

The synthesis indicates that while IEG All provides the foundational AI tools and broad social theories, EG Health provides the biological and regulatory context. IEG Health represents the synthesis of these two, applying advanced AI (like LLMs and Deep Learning) to specific healthcare challenges such as elderly care regulation and chronic disease diagnosis.

3.1. The Translation from EG Health and IEG All to IEG Health

The integration of Intelligent Evolutionary Games (IEG) into the healthcare sector necessitates a multidimensional transposition of existing theoretical frameworks. This process involves the systematic recalibration of four core pillars: the themes of social governance, the contextual shift of health domains, the underlying logic of strategic interaction, and the computational engines of Artificial Intelligence. The following analysis explores the transition from static evolutionary dynamics to adaptive learning strategies, ensuring that AI-driven healthcare systems remain resilient, secure, and patient-centric.

The Translation of Social Governance Themes: Foundational IEG constructs, such as Reputation Management and Trust Evaluation, are operationalized within the medical context as "Clinician AI-Adoption" and "Patient Digital-Health Trust." Within the IEG Health framework, the "intelligent" component enables the simulation of trust trajectories as they evolve in response to AI-generated clinical interventions. Furthermore, traditional themes of Public Participation and Governmental Supervision are translated into the "dynamic regulation of community-based elderly care." While traditional models address policy at a macro level, IEG Health introduces an algorithmic layer, utilizing data-driven heuristics to regulate these services in real-time.

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The Contextual Shift of Health Domains: The transition across health domains involves an ontological shift from passive biological processes to autonomous agent-based simulations. Traditional biological conflicts—such as oncological evolution, pathogen drug resistance, and disease transmission—are re-contextualized by replacing passive entities with intelligent agents:

- **From Drug Resistance to AI-Augmented Chronic Disease Management:** Rather than modeling stochastic bacterial evolution, IEG Health models how a patient's "intelligent" wearable interface adaptively modifies treatment schedules to preemptively mitigate resistance.
- **From Privacy Protection to Adaptive Security in Smart Environments:** This entails a shift from static regulatory compliance to the implementation of self-evolving, AI-driven security protocols designed to safeguard sensitive health telemetry within smart-home ecosystems.

The Logic of Strategic Interaction: The mathematical foundations of IEG—including the Prisoner's Dilemma, Nash Equilibrium, and Stackelberg Games—are augmented through the integration of machine intelligence. In conventional health-based evolutionary games, Replicator Dynamics are typically characterized by fixed differential equations. In contrast, IEG Health transposes these into Adaptive Learning Strategies. For example, a "Hawk-Dove" game applied to healthcare resource allocation is reconfigured as a Deep Reinforcement Learning (DRL) problem, wherein agents (such as hospitals or autonomous systems) converge toward equilibrium through iterative trial-and-error and environmental feedback.

Intelligent Computational Engines: The most critical architectural translation involves the deployment of specialized AI paradigms to drive the IEG Health engine:

- Federated Learning: This facilitates the training of robust diagnostic models across heterogeneous hospital networks while maintaining data siloization, thereby addressing the core theme of privacy.
- Multi-Agent Reinforcement Learning: This is utilized to model the high-dimensional interactions between diverse stakeholders within chronic disease or smart-home ecosystems.
- Swarm Intelligence: This paradigm is applied to surgical robotics and decentralized diagnostic networks, where coordinated units collaborate heuristically to execute complex medical tasks.

3.2. Case Study

To demonstrate how Social Trust from IEG All might translate into Doctor Adoption of AI in IEG Health, we look at it as a intelligent evolutionary game where the "players" (the doctor and the AI) must reach a stable equilibrium of cooperation. In the broader IEG All context, trust is a general metric for system stability. In IEG Health, this becomes a high-stakes "Evolutionary Game" with clinical consequences (Table 2).

Table 2. The Translation: From Theory to Clinical Reality.

Concept in IEG All (Social Trust)	Translation to IEG Health (Doctor Adoption)	The Intelligent Logic (Mechanism)
Reputation Management	Algorithm Transparency	Doctors assess the AI's "reputation" based on past diagnostic accuracy and explainability (XAI).
Cooperation Dynamics	Human-AI Collaboration	The game moves from "Human vs. AI" to a "Human + AI" team, where the payoff is the patient's recovery.
Trust Evaluation	Reliability Assessment	Using Bayesian Learning, the doctor updates their trust in the AI after every successful or failed intervention.

In this IEG Health scenario, we model the interaction as an Adaptive Coordination Game (Figure 5):

1. The Players: The Clinical Specialist (Expertise-driven) and the AI Diagnostic Agent (Data-driven).
2. The Strategy: * Doctor: Choose to Adopt (Follow AI advice) or Override (Use intuition).

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- AI: Provide High-Confidence or Low-Confidence output.

3. The Intelligent Twist: Unlike a static game, this uses MARL. The AI "learns" the doctor's preferences and risk tolerance, while the doctor "learns" the AI's strengths.

Why This Translation Matters

- Preventing "Deskilling": If trust is too high (blind adoption), doctors may lose their critical skills.
- Reducing "Algorithm Aversion": If trust is too low (constant override), the benefits of AI in reducing human error are lost.
- Finding the Nash Equilibrium: The goal is to find the point where the doctor uses the AI only when the AI's "Intelligence" truly exceeds human pattern recognition.

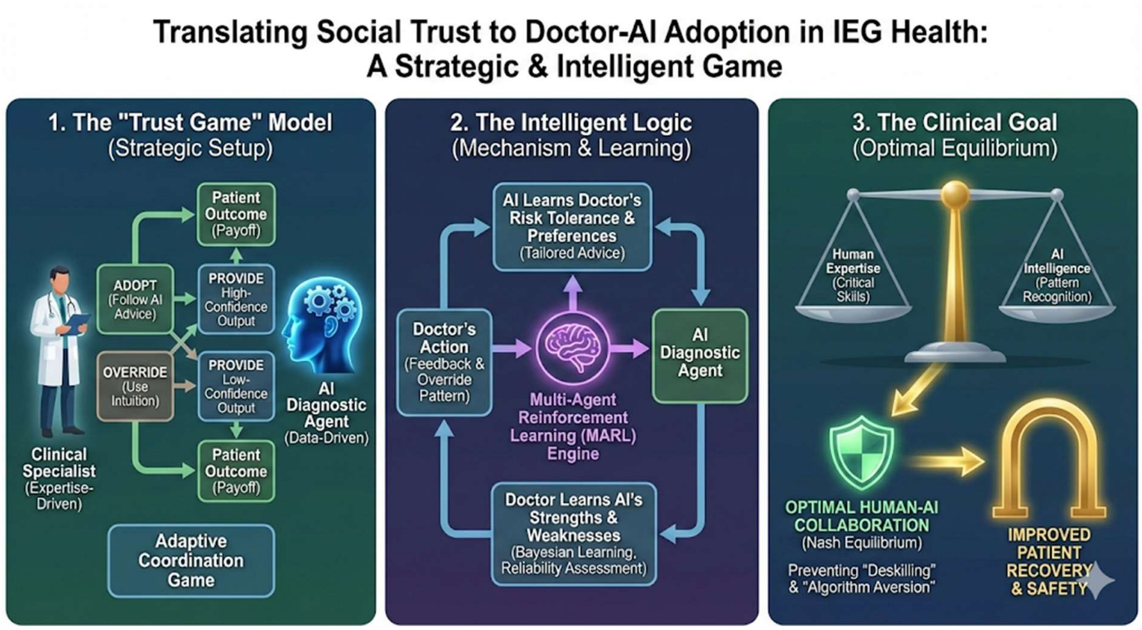

Figure 5. Translating social trus to Doctor-AI Adoption.

4. Conclusions

This research has systematically mapped the "near-empty" landscape of Intelligent Evolutionary Games in healthcare, revealing a profound disparity between theoretical AI-EGT models and their clinical application. By implementing the SNER framework, we have demonstrated that the "knowledge void" in IEG Health can be bridged through the strategic translation of established paradigms from social governance and general intelligence.

Our findings underscore that the transition to IEG Health necessitates an ontological shift: moving from passive biological modeling—such as stochastic drug resistance—to autonomous, agent-based simulations where AI entities and human practitioners co-evolve. The case study on Doctor-AI Adoption illustrates that trust is not a static prerequisite but a dynamic Nash Equilibrium achieved through Multi-Agent Reinforcement Learning (MARL) and iterative Bayesian updates.

Ultimately, the integration of IEG into healthcare offers a robust mechanism for regulating community-based care, optimizing chronic disease management, and fostering human-AI synergy. Future research should focus on the "Adaptive Oncology" path and the deployment of Federated Learning to resolve the tension between data privacy and the need for high-dimensional strategic modeling. By treating the clinical environment as an adaptive coordination game, the healthcare sector can leverage IEG to ensure that AI adoption is both resilient and patient-centric.

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