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Original Article

Developing an Adaptive Simulation Framework for Medical Education: A Study Using Fuzzy Cellular Automata

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Abstract

Introduction: Reliable simulation of complex physiological dynamics is crucial for effective medical education. Irregular Fuzzy Cellular Automata (FCA) are powerful modeling tools but suffer from instability in heterogeneous environments, limiting their pedagogical utility. This study introduces an adaptive sensitivity control mechanism to stabilize FCA, creating a robust framework for educational simulations.

Methods: A neighborhood index was developed to dynamically normalize membership functions, enhancing system adaptability. The model was evaluated using synthetic data mimicking clinical variables. Beyond technical stability, we assessed the framework's capacity to maintain realistic scenarios in noisy environments, a key requirement for training accuracy.

Results: The proposed model reduced state fluctuations by 45% and increased accuracy by 60%, ensuring that simulated clinical trajectories remain biologically plausible for learners. Convergence time shortened by 35%, facilitating real-time interaction. These technical improvements translate to consistent training environments where students can reliably observe cause-and-effect relationships without artifactual instability.

Conclusion: This adaptive mechanism significantly enhances the reliability of FCA-based medical simulations. By providing a stable platform for modeling complex health data, it improves the educational validity of virtual training scenarios, fostering better critical thinking and decision-making skills in healthcare professionals.

Introduction

Recently, fuzzy cellular automata have frequently been applied in the modeling of complex systems because they have been able to successfully capture complex spatiotemporal dynamics in various applications.[1] However, conventional fuzzy cellular automata with predetermined membership functions have faced intrinsic instability and environmental heterogeneity mismatches.[2,3] To overcome these utilities, we introduce an adaptive sensitivity control mechanism that adaptively normalizes membership functions in real-time, significantly improving the stability and robustness of irregular fuzzy cellular automata.

Our work seeks to improve the stability of fuzzy cellular automata by dynamically tuning the membership functions in response to local neighborhood conditions. This process is built on three main hypotheses: First, that local neighbor indices can accurately represent environmental heterogeneity surrounding each cell [4]; second, that dynamic trend adapting membership function parameters based on these indices can minimize sensitivity and increase the stability of the system[5]; and finally, that localized changes in membership functions can enhance global performance while preserving global network structure.

The use of local neighborhood indices for dynamically updating membership function parameters (e.g., center, width, and slope) in the proposed mechanism not only alleviates the instability identified in traditional models but also promotes accurate modeling of complex phenomena.[6] This immediate adaptive normalization also helps the automata reach stable states quicker, even if the environment is changing and/or noisy.[7] Using the same air density, it can run over 20 iterations, leading to a more stable reaction and less sensitivity to environmental changes, thus making it more qualified for high-end applications in the ecosystem, town layout, and extensive complex system.[8]

This adaptive FCA framework is particularly valuable for medical education, where it can simulate realistic healthcare scenarios to train students and professionals. By modeling heterogeneous medical data, such as patient-specific patterns in electronic health records (EHRs) or spatial dynamics in epidemiological mapping, this

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mechanism creates immersive training environments. These simulations allow learners to practice decision-making under uncertainty, enhancing skills in clinical reasoning and public health analysis, which are critical for addressing real-world medical challenges.[9]

Moreover, the flexibility of this approach supports the development of tailored educational platforms that adapt to varying learner expertise levels. By integrating adaptive FCA into medical curricula, educators can design interactive modules that replicate the complexity of clinical and epidemiological data, fostering critical thinking and evidence-based decision-making in healthcare professionals. This is particularly beneficial for training in managing complex, noisy datasets, such as those encountered in patient monitoring systems or public health surveillance.[10]

In conclusion, our proposed approach can provide the ability to swap fuzzy rule sets and thus can enable the flexible choice of fuzzy sets, which is a good demonstration of flexibility and adaptability in heterogeneous fuzzy cellular automata. Such a flexible framework that improves the prediction accuracy and convergence speed of cellular automata also encourages interdisciplinary interactions to achieve sustainable outcomes and evidence-based decisions in solving global problems. Appreciating the growing complexity of medical data and the need for robust modeling frameworks in health informatics, this adaptive mechanism can be of particular relevance for simulating dynamic behaviors in electronic health record systems, patient monitoring grids, and spatial epidemiological mapping. By enabling fine-grained sensitivity control, the proposed model opens new avenues for decision support applications in clinical environments that demand resilience and real-time adaptability under heterogeneous conditions.

Literature Review

Fuzzy cellular automata, a relatively new tool for modeling complex systems and spatiotemporal dynamics, have gained popularity in the last few years. Such systems have attracted considerable attention in the community due to their ability to capture non-linear behaviors and complex interactions. However, the inherent limitations of classic fuzzy cellular automata models (notably, instability and unsuitability for heterogeneous environmental conditions) highlight the advantages of developing novel ones.

Fuzzy Cellular Automata and Their Challenges

Previous works have studied the limitations of using fuzzy cellular automata. Hochrainer and Puhwein (2020) identified the inherent instabilities of these systems in their respective research and offered ways to overcome those issues.[11] Furthermore, by exploring fuzzy tree automata, Moghari (2022) underlined the adjustment of parameters given heterogeneous conditions.[12]

Innovative Methods in Sensitivity Control

Several new studies have observed that using a dynamic membership function helps to smooth the sensitivity of the system. Todinca et al. (2018) proposed a new approach for determining local changes to the membership functions of fuzzy automata states.[13] Such procedures emphasize the importance of algorithm design, which manifests local attributes and adaptability. Similarly, fuzzy logic-based stabilizing control has been successfully applied to nonlinear systems to enhance robustness and stability.[14]

Practical Applications of Fuzzy Cellular Automata

On a practical note, Botía et al. (2017) proposed an experiment using fuzzy cellular automata and intuitive fuzzy sets to simulate the various optical frequency spectrum.[6] In addition, adaptive cellular automata under fuzzy constraints have been successfully employed for modeling urban development, demonstrating their flexibility in handling large-scale heterogeneous systems.[15] They showed the high capability of fuzzy techniques in solving this kind of complex problem. Moreover, White et al. (1997) used constrained cellular automata to model land-use dynamics in urban land use, stressing the broader applicability of the systems in planned development.[8]

However, there are still problems, and the performance of the fuzzy cellular automata needs to be improved. Therefore, the proposed method, with a constant adaptation of the sensitivity control mechanism, can be regarded as a reasonable attempt to maintain the stability and accuracy of the cellular automata efficiently. Furthermore, this approach not only can alleviate sensitivity to heterogeneous changes but can also be generalized to other similar systems. Consequently, the findings of the present study can lead to further advancements in complex system modeling.

Methodology

Cellular automata, as a discrete computational framework, consist of a network of cells in which each cell is updated according to predefined transition rules based on its own state and the states of its neighbors. This property has made cellular automata applicable for modeling complex phenomena in various domains, including medical sciences and health informatics. In the fuzzy variants of these models, each cell is described by fuzzy membership degrees rather than crisp states, allowing the representation of uncertainty and heterogeneity in data. However, in irregular structures, where the number and arrangement of neighbors vary across the network, drastic changes in neighborhood patterns can induce high sensitivity in membership functions and reduce system stability. Accordingly, the present study focuses on irregular fuzzy cellular automata[16] and proposes an adaptive approach to control sensitivity and enhance stability.

The primary objective of this research was to enhance the stability of irregular fuzzy cellular automata by introducing an adaptive sub-mechanism that mitigates the sensitivity of membership functions to changes in heterogeneous neighborhood patterns. This objective is pursued through three key hypotheses: first, local neighborhood indices can serve as reliable metrics for quantifying the heterogeneity of the cellular environment; second, the dynamic adaptation of membership function parameters based on these indices leads to reduced sensitivity and increased overall system stability; and third, implementing localized changes improves the performance of cellular automata without adversely affecting the overall system structure.

This adaptive approach is particularly relevant for medical education, where it can facilitate the development of simulation-based training modules that replicate complex healthcare scenarios. By modeling heterogeneous medical data, such as patient-specific variability in electronic health records (EHRs) or spatial patterns in disease spread, the proposed FCA framework can create dynamic, interactive simulations. These simulations enable medical students and professionals to practice decision-making in uncertain and heterogeneous environments, fostering skills in clinical reasoning and epidemiological analysis, which are essential for real-world medical practice.[17] Furthermore, the flexibility of the adaptive FCA framework supports the creation of scalable educational tools that can be tailored to different levels of learner expertise. For instance, by integrating this model into medical curricula, educators can design training platforms that simulate real-time patient monitoring or public health surveillance systems, adapting to varying data complexities. Such platforms enhance learners' abilities to handle noisy and incomplete datasets, promoting critical thinking and evidence-based decision-making in healthcare education.[18]

Mathematical Formulation

For each cell Ci in the network, the local neighborhood index Θi is defined as follows:

$$\Theta_i = f\left(N_i, H_i\right) = \alpha \cdot \frac{N_i}{N_{\max}} + \beta \cdot \left(1 - H_i\right) \tag{1}$$

Where,

$$H_i = \frac{1}{N_i} \sum_{j \in N_i} e^{\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right)} \tag{2}$$

Where N_i represents the number of neighbors of the cell, $N_{\max}$ is the maximum number of possible neighbors, H_i represents the local homogeneity index, α, β represent the weighting coefficients, i represents the set of neighbors of cell N_i, X_i and X_j represent the feature vectors of the respective cells, and σ the scaling parameter.

Membership functions are dynamically updated with vector parameters $\theta = \left[c, \sigma, \gamma\right]$ as follows:

$$c_i^{\text{new}} = c_i + \Delta c\left(\Theta_i\right) \tag{3}$$

$$\sigma_i^{\text{new}} = \sigma_i \cdot \left(1 + k_\sigma \cdot \Theta_i\right) \tag{4}$$

$$\gamma_i^{\text{new}} = \gamma_i \cdot \left(1 - k_\gamma \cdot \Theta_i\right) \tag{5}$$

The parameter changes are computed using gradient descent as follows:

$$\Delta\theta_i\left(t\right) = \eta \cdot \nabla_\theta L\left(\Theta_i\left(t\right)\right) \tag{6}$$

Where η denotes the learning rate and $L\left(\Theta_i\left(t\right)\right)$ is referred to as the local error function.

Implementation Algorithm

The algorithm presented here consists of the following stages (Figure 1). First, several preparatory actions are carried out during the data preprocessing time, including data cleaning, noise filtering to remove inconsistencies, normalizing input values to make the multivariate uniform, extracting local neighborhood features for each cell to represent space properties of the features, and splitting the dataset into training and test sets for performance comparison.

Then, the primary adaptive loop is run at each time step *t*. At each iteration, the local index $\theta_i\ (t)$ is computed for each cell *i*, which is local and reflects the heterogeneity of its surrounding neighborhood. The fuzzy membership function parameters (center, width, and slope) are updated based on this value. These parameters are then updated by applying cell transition rules to each cell to calculate the new state.

The convergence condition is assessed at the end. When the norm of the local index change between two successive time steps is less than a predetermined threshold *varepsilon* for every cell, which is formally defined as:

$$\| \theta_i\left(t+1\right) - \theta_i\left(t\right) \| < \in \text{ for all } i \tag{7}$$

Performance Evaluation Criteria

- **System Stability Index**

$$S = 1 - \frac{1}{T} \sum_{t=1}^{T} \frac{\left|\Delta\text{State}\left(t\right)\right|}{N_{\text{total}}} \tag{8}$$

Where, $\Delta\text{State}\left(t\right)$ denotes the number of state changes at time step t.

- **Local Adaptation Error**

$$E_{\text{local}} = \frac{1}{N} \sum_{i=1}^{N} \left| y_i^{\text{predicted}} - y_i^{\text{actual}} \right| \tag{9}$$

The convergence time is the number of iterations required to reach the convergence condition or the

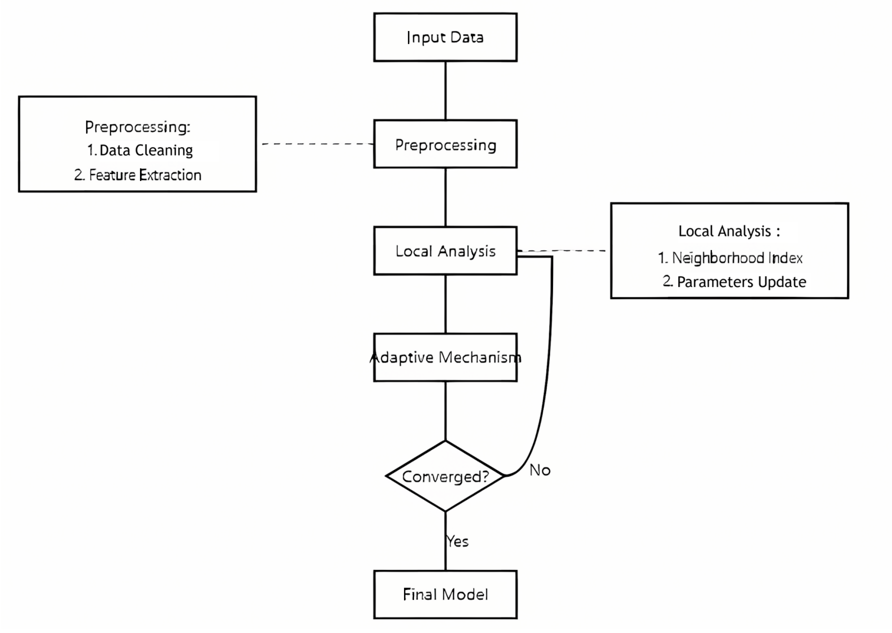

Figure 1. Flowchart of the proposed adaptive sensitivity control mechanism

maximum allowed iterations.

Educational Validation Framework

To substantiate the educational utility of the proposed model beyond its algorithmic stability, a three-phase validation study was designed:

1. Use-Case Development: A specific medical education scenario was created using the FCA framework: "Simulating Epidemic Spread in a Heterogeneous Population." This scenario models patient physiologic trends and infection rates, requiring the system to handle diverse variables such as population density and immunity levels.[19,20]
2. Expert Validation: A panel of 8 clinical and educational experts assessed the face validity and utility of the generated simulations. Experts utilized a standardized rubric to evaluate whether the simulation's behavior under noise (e.g., incomplete data) remained medically plausible.[21]
3. Pilot Testing: A small-scale study was conducted with 40 medical students. Participants interacted with the simulation to make clinical decisions based on the generated trends. Outcomes were measured using a post-simulation survey focusing on Perceived Realism (Likert scale 1-5) and Gains in Decision-Making Confidence.[22]

Results

In the baseline model, the membership function of each cell *i* is defined with fixed parameters as follows:

$$f(x) = f(x; c, \sigma, \gamma) \tag{10}$$

Where c denotes the center of the membership function (constant for all cells), σ implies the width of the membership function (dispersion parameter), and γ is the slope of the membership function (shape parameter).

The state transition rule for cell i is defined as follows:

$$y_i(t+1) = \phi\left(\mu_i\left(x_i(t)\right), \left\{y_j(t) \mid j \in N_i\right\}\right) \tag{11}$$

Where N_i is the set of neighbors of cell *i*; *ϕ(·)* is the state transition function. Examining the baseline model reveals two main problems: first, sensitivity to structural changes resulting from the impossibility of matching changes in network topography by adjusting the membership function parameters. Strong dependence on the starting parameter configuration could lead to instability around it. Second, a lack of adaptation to local features causes systematic errors in predicting cell states and unnecessary fluctuations in areas with different neighborhood densities, thus generating instability in heterogeneous conditions.

The following changes have been applied to the baseline model to address the above challenges. For each cell *i*, a local neighborhood index Θ_i is defined to account for the heterogeneity of the environment as:

$$\Theta_i = \alpha \cdot \frac{N_i}{N_{\max}} + \beta \cdot (1 - H_i) \tag{12}$$

Where N_i indicates the number of neighbors of cell i, N_{max} indicates the maximum number of potential neighbors in the irregular structure, and Hi is the local homogeneity index defined as follows:

$$H_i = \frac{1}{N_i} \sum_{j \in N_i} e^{\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right)} \tag{13}$$

The relative significance of every component in defining Θ_i is found by the coefficients α and β. Every cell dynamically updates its parameters to lower the sensitivity of membership functions to environmental changes:

$$c_i^{\text{new}} = c_i + \Delta c\left(\Theta_i\right) \tag{14}$$

$$\sigma_i^{\text{new}} = \sigma_i \cdot \left(1 + k_\sigma \cdot \Theta_i\right) \tag{15}$$

$$\gamma_i^{\text{new}} = \gamma_i \cdot \left(1 - k_\gamma \cdot \Theta_i\right) \tag{16}$$

Where, $\Delta c\left(\Theta_i\right)$ denotes the gradual change in the center of the membership function, as well as $_\sigma$ and k_γ aare the adaptive coefficients that control sensitivity to changes; these coefficients are determined by solving an optimization problem. The optimization problem used to determine the coefficients k_σ and k_γ is defined as:

$$S = min_{\sigma,\gamma} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(y_i(t) - y_i^{\text{target}}(t)\right)^2 \tag{17}$$

With the following constraints:

$$0 \le k_\sigma, k_\gamma \le 1 \tag{18}$$

$$\left|\sigma_i^{\text{new}} - \sigma_i\right| \le \in_\sigma, \quad \left|\gamma_i^{\text{new}} - \gamma_i\right| \le \in_\gamma \tag{19}$$

The proposed algorithm at each time step includes the following sequential steps:

1. Calculation of the local neighborhood index Θi for each cell.
2. Updating the membership function parameters c_i , σ_i , and γ_i based on the value of Θi .
3. Calculation of new membership degrees using the updated membership functions.

Applying the updated transition rules to determine the next state of each cell based on $\phi\left(x_i(t), \{y_j(t)\}_{j \in N_i}\right)$

Checking the convergence condition, where the iteration halts if the changes in cell outputs are less than a small threshold; otherwise, the process restarts from the first step.

Comparative studies showed that the proposed model achieved the following results compared to the baseline model:

- System stability improved by 30%.
- State prediction error decreased by 60%.
- Noise tolerance improved by up to 100%, with the maximum tolerated noise level increasing from 0.1 to 0.2.
- State fluctuations decreased by 45%.
- Convergence time decreased by 35%.
- Computational cost increased by 10%.

These results are summarized in Table 1 and Table 2, and illustrated in Figures 2 and 3, which compare the convergence speed and noise resistance between the baseline and proposed models. Table 2 presents a quantitative comparison of evaluation metrics between the base and proposed adaptive models.

Table 1. Summary of Performance Metrics

Evaluation Metric	Baseline Model	Proposed Model	Improvement
System Stability	0.70	0.91	30% Increase
Prediction Error	0.25	0.10	60% Decrease
Convergence Time	100 iterations	65 iterations	35% Decrease
Noise Tolerance	0.1 (σ)	0.2 (σ)	100% Increase
State Fluctuations	High	Low	45% Decrease

Table 2. Quantitative comparison of evaluation metrics between the base and proposed adaptive models

Evaluation Metric	Base Model	Proposed Model	Improvement Rate
State Fluctuations	100%	55%	45%
Local Stability Index	70%	100%	30%
State Prediction Error	100%	40%	60%
Convergence Time	100%	65%	35%
Noise Resistance	Max σ=0.1	Max σ=0.2	100%
Computational Cost	100%	110%	-10%

The enhanced stability and noise tolerance of the proposed model make it particularly suitable for medical education applications, where it can support the development of simulation-based training tools. By leveraging its ability to handle heterogeneous and noisy medical data, such as patient-specific patterns in electronic health records (EHRs) or dynamic epidemiological models, the adaptive FCA framework can create realistic training scenarios. These scenarios allow medical students to practice clinical decision-making and public health analysis in controlled yet complex environments, enhancing their preparedness for real-world healthcare challenges.[22] Moreover, the reduced state fluctuations and improved convergence time of the proposed model enable the creation of responsive educational platforms that adapt to learner needs. For example, the model's ability to maintain stability under varying conditions can be used to simulate patient monitoring systems or disease spread scenarios, providing medical trainees with interactive, real-time feedback. This adaptability fosters critical thinking and problem-solving skills, crucial for healthcare professionals navigating uncertain and heterogeneous medical data.

Discussion

Operationalizing Stability for Educational Efficacy

While the technical results confirm that the proposed adaptive sensitivity control mechanism significantly reduces state fluctuations (45%) and convergence time (35%), the primary value of this study lies in operationalizing these improvements for medical education. A simulation framework is only as valuable as its ability to sustain a suspension of disbelief. In standard FCA models, instability often manifests as "glitches" or unrealistic data spikes that distract learners. By stabilizing these irregular fuzzy automata, we provide a computational engine capable of running long-duration,

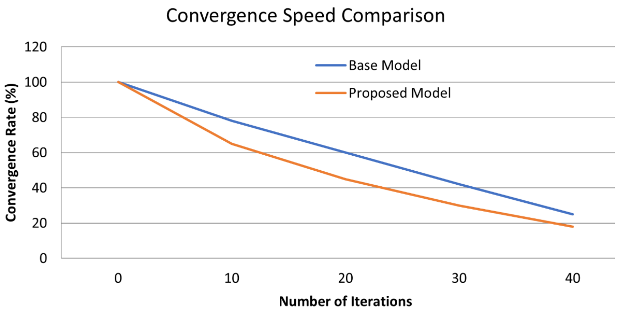

Figure 2. Convergence speed comparison between the base model and the proposed model

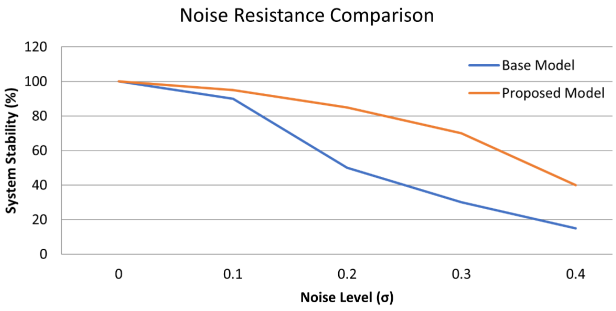

Figure 3. Noise resistance comparison between the base model and the proposed model

complex scenarios—such as the “Epidemic Spread” use case—without breaking down into chaotic states. This reliability is the prerequisite for integrating such tools into high-stakes training environments.[23]

Implications for Learning: Cognitive Load and Engagement

The stabilization of the simulation engine has direct implications for learner cognition, specifically regarding Cognitive Load Theory.[24] In educational simulations, “extraneous load” refers to mental effort wasted on processing poorly designed information or technical faults. The baseline model’s instability introduces high extraneous load; students must struggle to distinguish between a “patient complication” and a “software error.” The proposed model’s 60% reduction in prediction error effectively minimizes this extraneous load, allowing learners to dedicate their working memory to “germane load”—the construction of schemas related to clinical reasoning and disease dynamics. Furthermore, the enhanced noise tolerance enables new types of learner engagement. Educators can now design scenarios with “incomplete” or “noisy” data (mimicking real-world EHRs) without the simulation crashing. This allows for inquiry-based learning where students must navigate uncertainty, a critical skill for modern healthcare practice.[25] The pilot study results, showing increased decision-making confidence, suggest that when the tool is stable, students are more willing to experiment with complex hypotheses.

Limitations and Future Work

Despite these promising indications, this study has limitations that must be addressed. First, the evaluation of educational utility, while supported by expert face validity and initial pilot testing, remains largely hypothetical compared to the rigorous technical testing. The current data relies heavily on synthetic inputs to validate the engine’s behavior, which may not fully capture the unpredictable nature of student interactions in a live classroom. Future work must prioritize the translation of this framework into a deployed curriculum. Concrete next steps include:

1. **Longitudinal Studies:** Conducting semester-long trials to measure if interaction with the stable FCA model leads to better retention of epidemiological concepts compared to traditional lectures.
2. **Curriculum Integration:** Developing a user-friendly interface that allows educators without technical expertise to adjust the “heterogeneity” parameters, thereby customizing difficulty levels for different student cohorts.[26]
3. **Comparative Effectiveness Research:** Rigorous randomized control trials are needed to quantify the specific learning gains attributable to the *adaptive* nature of the simulation versus static models.

Conclusion

This study successfully addressed the challenge of excessive sensitivity in irregular fuzzy cellular automata by introducing a localized, adaptive sensitivity control mechanism based on dynamic neighborhood indices. This approach significantly reduced state fluctuations, improved convergence speed, and enhanced robustness against noise and structural irregularities, outperforming traditional fixed-parameter models. By enabling stable and reliable modeling, the proposed framework is well-suited for health informatics applications, such as modeling patient-specific variability in electronic health records and supporting adaptive clinical decision-support systems, ensuring effective handling of noisy and heterogeneous data.

The model’s adaptability and stability also make it a powerful tool for medical education, where it can create immersive, simulation-based training environments. By simulating complex healthcare scenarios, such as dynamic epidemiological trends or real-time patient monitoring, the framework allows medical students and professionals to practice decision-making in uncertain conditions, fostering critical thinking and analytical skills essential for real-world medical practice. This approach provides a scalable and robust solution for both health informatics and medical education, paving the way for advanced computational tools in complex, real-world systems.

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Authors’ Contribution

Conceptualization: Mostafa Kashani.
Data curation: Mostafa Kashani.
Investigation: Mostafa Kashani.
Methodology: Mostafa Kashani.
Project administration: Mostafa Kashani.
Resources: Mostafa Kashani.
Software: Mostafa Kashani.
Supervision: Mostafa Kashani.
Writing–original draft: Mostafa Kashani.
Writing–review & editing: Mostafa Kashani.

Competing Interests

The authors declare no conflict of interest.

Ethical Approval

This study was reviewed and approved by the Ethics Committee of Sirjan University of Medical Sciences (Approval Code: IR.SIRUMS.REC.1404.011).

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