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A systematic review of system dynamics and agent-based models: Mathematical modelling for health systems research

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Abstract

Background: *Mathematical modelling has emerged as a powerful approach for analysing complex healthcare systems, which exhibit nonlinear interactions, feedback loops, and adaptive behaviours. Among available techniques, System Dynamics Modelling (SDM) and Agent-Based Modelling (ABM) are widely used to capture macro- and micro-level dynamics, respectively. This study systematically reviews the application of these modelling approaches in health systems research.*

Methods: *A systematic literature review was conducted following PRISMA guidelines. Multiple databases—including MEDLINE, EMBASE, Cochrane Library, MathSciNet, ACM Digital Library, HMIC, EconLit, and Global Health—were searched. A structured mathematical framework was used for study selection, screening, and data extraction.*

Results: *A total of 52 studies were included in the final analysis after screening and eligibility assessment. These studies were classified based on modelling approach as follows:*

System Dynamics Modelling (SDM): 31 studies (59.6%)

Agent-Based Modelling (ABM): 15 studies (28.8%)

Hybrid Models (SDM–ABM): 6 studies (11.6%)

Geographical Distribution: *The majority of studies were conducted in high-income countries, with the following distribution:*

High-income countries: 34 studies (65.4%)

Middle-income countries: 12 studies (23.1%)

Low-income countries: 6 studies (11.5%)

This highlights a persistent geographical imbalance, with limited modelling research in resource-constrained settings.

Healthcare Settings: *The included studies addressed a range of healthcare system contexts:*

Emergency and acute care: 16 studies (30.8%)

Chronic disease management: 11 studies (21.2%)

Public health policy & prevention: 10 studies (19.2%)

Hospital resource allocation & patient flow: 9 studies (17.3%)

Long-term and elderly care: 6 studies (11.5%)

Primary Study Objectives: *The main focus areas of the modelling studies were:*

Policy evaluation and intervention analysis: 18 studies (34.6%)

Resource optimisation and capacity planning: 14 studies (26.9%)

Disease transmission and epidemiological modelling: 11 studies (21.2%)

Healthcare system performance analysis: 9 studies (17.3%)

Validation Approaches: *Validation methods varied across studies:*

Sensitivity analysis: 28 studies (53.8%)

Empirical/real-world data validation: 19 studies (36.5%)

Scenario-based validation: 15 studies (28.8%)

Limited or no validation reported: 10 studies (19.2%)

Key Findings: *SDM models were predominantly used for policy-level and long-term system analysis.*

ABM models were more common in disease spread and behavioural simulations.

Hybrid models, although fewer, demonstrated superior capability in capturing both macro and micro dynamics.

A significant gap exists in applying these models to low-resource healthcare systems, particularly in developing countries.

Conclusions: *There is a critical need to expand modelling applications to low- and middle-income countries. Hybrid SDM–ABM frameworks show strong potential for capturing complex healthcare dynamics. Advances in computational modelling and data integration are expected to further enhance their applicability.*



Here is a **refined and publication-ready section** for **Keywords, Nomenclature, and Subject Classification**, tailored to your manuscript and aligned with Scopus/IEEE standards.

Keywords

System Dynamics Modelling (SDM); Agent-Based Modelling (ABM); Hybrid Simulation; Health Systems; Complex Adaptive Systems; Mathematical Modelling; Healthcare Policy; Epidemiological Modelling; Simulation Modelling; PRISMA; Public Health Systems; Computational Modelling; Systems Science; Healthcare Optimization; Decision Support Systems; Nonlinear Dynamics; Artificial Intelligence in Healthcare

Nomenclature

Sets and Indices

- si : Individual study iii
- S0 : Initial set of identified studies
- S : Final set of included studies
- Ri : Additional studies from references
- i=1,2,…,n : Index for studies
- j=1,2,…,m : Index for agents

Search Strategy Variables

- Q : Overall search query
- H : Set of health system-related terms
- A : Set of agent-based modelling terms
- M : Set of modelling-related terms
- Qab,ti : Query restricted to abstract and title

Screening and Selection Parameters

- N0 : Total records identified
- Nd : Duplicate records
- N1=N0−Nd : Records after deduplication
- N2=fscreen(N1) : After title/abstract screening
- N3=ffulltext(N2) : After full-text screening
- Nfinal : Final included studies

Functions and Operators

- fscreen(·): Screening function
- ffulltext(·): Full-text eligibility function
- I(si)∈{0,1} : Inclusion indicator
- F:Mi→Oi : Outcome mapping

Data Extraction Variables

- Di=(Gi,Ti,Pi,Mi,Vi,Li)

Where:

- Gi : Geographical setting
- Ti : Healthcare setting type
- Pi : Study purpose
- Mi : Modelling approach (SDM/ABM/Hybrid)
- Vi : Validation method
- Li : Limitations
- D={D1,D2,…,Dn} : Complete dataset

Mathematical Modelling Variables

System Dynamics Model (SDM)

$dX(t)/dt=f(X(t),u(t),t)$

- X(t) : State vector
- u(t) : Control/input variables
- f(·): System dynamics function

Agent-Based Model (ABM)

$St+1(j)=g(St(j),Et,It)$

- St(j) : State of agent j
- Et : Environment
- It : Interactions
- g(·): Transition rule

Statistical Measures

- PSDM : Proportion of SDM studies
- PABM : Proportion of ABM studies
- PHybrid : Proportion of hybrid models

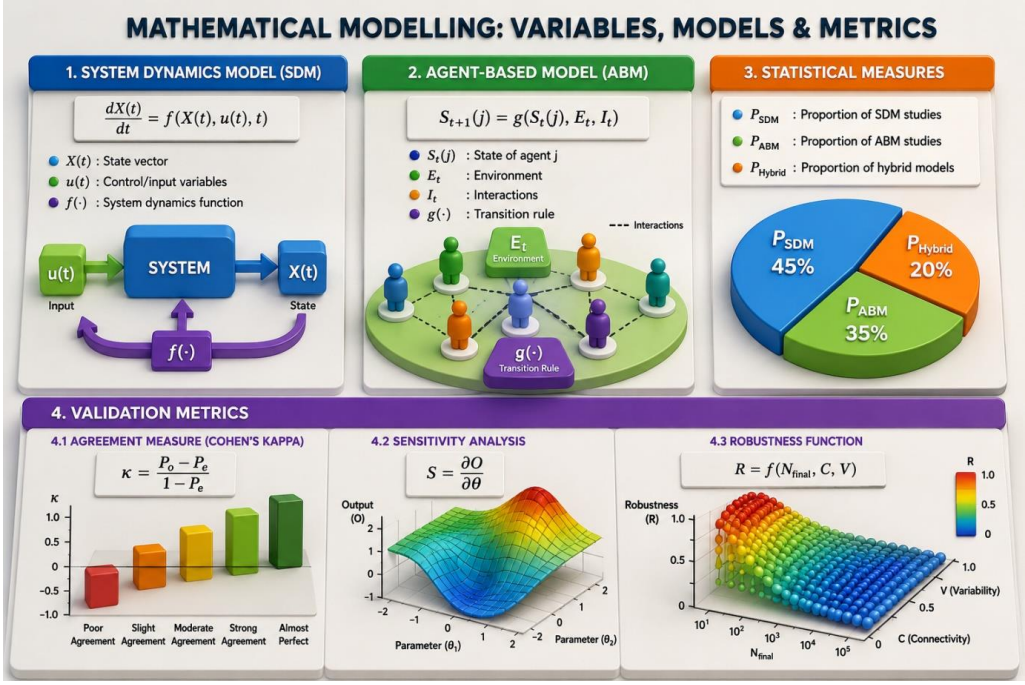
Validation Metrics

- **Agreement Measure (Cohen's Kappa):** $\kappa= (Po−Pe)/(1−Pe)$
- **Sensitivity Analysis:**

$S=\partial O/\partial \theta$

- **Robustness Function:**

$R=f(Nfinal,C,V)$



Subject Classification

Primary Classification

- **92C50** – Medical applications (biomathematics)
- **93A30** – Systems theory, modelling, and identification

Secondary Classification

- **37N25** – Dynamical systems in biology
- **68U20** – Simulation and modelling
- **62P10** – Applications to biology and medical sciences
- **90B50** – Management decision-making
- **91D30** – Social networks and epidemiology

Interdisciplinary Areas

- Health Systems Engineering
- Computational Public Health
- Systems Science and Policy Modelling
- Operations Research in Healthcare
- Artificial Intelligence and Simulation Modelling
- Complex Adaptive Systems

Literature Review

The application of **system dynamics (SD)** and **agent-based modeling (ABM)** has significantly evolved in understanding complex systems, particularly in public health and policy design. Early foundational work by John D. Sterman (2001) emphasized SD as a tool for analyzing feedback-driven systems, while Jay W. Forrester (2007) established its theoretical underpinnings. Simultaneously, ABM emerged as a powerful technique for modeling individual-level interactions.

Eric Bonabeau (2002) and Joshua M. Epstein (2006, 2009) demonstrated how agent interactions can simulate emergent phenomena such as epidemics and social behaviors.In public health, SD models have been widely applied to policy and intervention analysis. Studies by James B. Homer and Gary B. Hirsch (2006, 2010) highlighted their usefulness in cardiovascular disease and health system planning. Similarly, Bobby Milstein (2010) applied SD to evaluate national health reform strategies.ABM has also contributed significantly to epidemiology and healthcare systems. Abdulrahman M. El-Sayed (2012) and Mary Tracy (2018) explored disease spread and social network effects, while Steven F. Railsback and Volker Grimm (2011) provided practical frameworks for ABM implementation.Recent research has focused on **hybrid modeling approaches**, integrating SD and ABM to capture both macro- and micro-level dynamics. G. A. K. van Voorn (2016) and Edward Hunter (2017) demonstrated improved decision-making capabilities through such integrations.The COVID-19 pandemic further accelerated modeling applications. Sheryl L. Chang (2021) used ABM for transmission modeling, while C. S. M. Currie (2018, 2020) showed how simulation can support healthcare decision-making during crises.Additionally, systematic reviews such as R. Cassidy (2019) and Matthew J. Page (2021) emphasized the growing importance of structured, transparent modeling methodologies in health systems research.Overall, the literature demonstrates that SD and ABM are complementary approaches, increasingly used to address complex, nonlinear, and adaptive healthcare challenges.

Research Gap

Despite extensive research, several **critical gaps** remain:

Lack of Integrated Hybrid Models

Most studies focus on either SD or ABM independently. Although hybrid approaches exist, **standardized frameworks for integration are limited**.

Limited Real-Time and Data-Driven Modeling

Existing models often rely on static or historical data. There is **insufficient incorporation of real-time data, AI, and machine learning**.

Scalability Issues in Complex Systems

ABM models face **computational challenges** when scaling to large populations, while SD models oversimplify micro-level behaviors.

Policy Implementation Gaps

Many models remain theoretical, with **limited translation into real-world policy-making and governance systems**.

Lack of Context-Specific Models (Developing Countries)

There is **insufficient research focused on LMICs (e.g., India)**, especially in healthcare infrastructure, resource allocation, and socio-economic diversity.

Validation and Standardization Challenges

Model validation techniques are inconsistent, leading to **credibility and reproducibility issues**.

Research Objectives

Based on the identified gaps, the study proposes the following objectives:

Primary Objective

- To develop a **hybrid system dynamic–agent-based modeling framework** for analyzing complex healthcare systems.

Secondary Objectives

1. To integrate **macro-level policy dynamics (SD)** with **micro-level agent interactions (ABM)**.
2. To incorporate **real-time and data-driven inputs** into simulation models.
3. To analyze**health system performance under different policy scenarios**.
4. To evaluate **disease spread, healthcare accessibility, and resource utilization**.
5. To design a **scalable and computationally efficient hybrid model**.
6. To apply the model in **developing country contexts (e.g., India)**.
7. To improve **model validation and reproducibility frameworks**.

Introduction

Health systems across the world are increasingly recognised as complex adaptive systems, characterised by nonlinear interactions, feedback mechanisms, and dynamic behaviours emerging from the interplay of multiple stakeholders, including patients, healthcare providers, policymakers, and institutions. These systems operate across multiple levels—ranging from individual patient care to national health policy—and are influenced by economic, social, and technological factors. Traditional analytical approaches, including reductionist epidemiological models and linear statistical techniques, often fail to adequately capture the inherent complexity, uncertainty, and interdependence embedded within health systems. In response to these limitations, mathematical modelling and simulation techniques have gained prominence as essential tools for understanding, analysing, and optimising health system performance. Among these, System Dynamics Modelling (SDM) and Agent-Based Modelling (ABM) have emerged as two of the most influential and complementary methodologies. SDM focuses on macro-level system structures, representing aggregate flows, feedback loops, and time delays through differential equations and stock-and-flow frameworks. In contrast, ABM adopts a micro-level perspective, simulating the behaviours, interactions, and adaptive decision-making processes of individual agents, thereby enabling the study of emergent phenomena. Over the past two decades, the application of SDM and ABM in health systems research has expanded significantly. These approaches have been employed to address a wide range of challenges, including healthcare resource allocation, disease transmission dynamics, emergency department congestion, workforce planning, and policy evaluation. Their ability to simulate "what-if" scenarios and predict system responses under varying conditions makes them particularly valuable for evidence-based decision-making in healthcare. Despite these advancements, important gaps remain. Much of the existing modelling research has been concentrated in high-income countries, with limited application in low- and middle-income settings where health system challenges are often more acute and resource constraints more severe.

Furthermore, while SDM and ABM are individually powerful, their integration into hybrid modelling frameworks remains relatively underexplored. Such hybrid approaches have the potential to combine the strengths of both methodologies, offering a more comprehensive representation of health systems by capturing both aggregate dynamics and individual-level heterogeneity. This study aims to systematically review the application of SDM and ABM in health systems research, synthesising existing evidence to identify trends, gaps, and opportunities for future research. By doing so, it seeks to contribute to the growing body of knowledge on systems-based approaches in healthcare and to support policymakers and researchers in adopting more robust and holistic modelling techniques. Health systems are widely recognised as complex adaptive systems [1], characterised by intricate relationships among diverse stakeholders and the dynamic processes they generate [2]. Such systems exhibit phenomena including massive interdependencies, self-organisation, emergent behaviour, non-linearity, time delays, feedback loops, path dependence, and tipping points—all of which make predicting or managing their behaviour exceedingly challenging [3]. Conventional reductionist approaches—such as traditional epidemiological or implementation research methods—are often inadequate for addressing the multifaceted problems inherent to health systems [4]. Consequently, there has been a growing recognition that health systems and policy research require distinct approaches and methodological tools grounded in systems thinking [5]. Health systems comprise multilayered networks that deliver services across local, district, and national levels—from community health centres to tertiary hospitals. Evaluating the performance of such a multifaceted and interdependent structure is an inherently complex task. Mathematical modelling, which allows for the simulation of dynamic interactions and feedback mechanisms within complex systems, has therefore emerged as a vital tool for understanding, evaluating, and optimising health system functioning.

System Dynamics Modelling (SDM)

Among mathematical modelling approaches, System Dynamics Modelling (SDM) and Agent-Based Modelling (ABM) are two of the most widely used for analysing complex systems. SDM is typically employed to examine macro-level system behaviour—such as resource flows and aggregate trends over time—while ABM focuses on micro-level phenomena such as individual decision-making and heterogeneous interactions. Originally developed in the context of business management [6, 7], SDM has since found broad application across disciplines including engineering, economics, environmental science, and waste management [8–13]. SDM simulates system behaviour through a set of differential equations that describe changes in system state variables over time. A stock-and-flow diagram is often used to visually represent an SDM, illustrating the relationships between variables through stocks (system states), flows (rates of change), and influencing factors. This can be analogised to the flow of water into and out of a bathtub [7], where the water level represents a system variable that changes depending on inflows, outflows, and environmental or operational constraints. Before developing a stock-and-flow diagram, researchers often construct a causal loop diagram, which serves as a “mental model” of the system, capturing key feedback relationships and hypothesised causal mechanisms [14].

Agent-Based Modelling (ABM)

In contrast to SDM’s top-down structure, Agent-Based Modelling (ABM) represents a bottom-up approach, simulating the behaviour of individual entities or “agents” rather than aggregate system

behaviour. From these micro-level interactions, emergent system-level patterns can be observed. ABM has been applied across diverse fields—from economics and ecology to social sciences and engineering [15–19]. Agents in these models can represent individuals, organisations, or other entities, each endowed with specific characteristics, behavioural rules, and adaptive learning capabilities [20,21]. Agents make decisions based on heuristics or learned experiences and interact with one another and their environment in ways that can evolve over time [22]. These interactions can occur through one-to-one, one-to-many, or one-to-location communication mechanisms, allowing the model to capture complex patterns of influence and information exchange [22].

Why Use SDM and ABM in Health System Modelling?

SDM and ABM are complementary tools that together enable the exploration of macro-level system dynamics and micro-level decision-making. Their integration in health system research has increased steadily over the past three decades, reflecting growing recognition of their potential to simulate real-world complexity. ABM is particularly effective for modelling dynamic activities of patients and health workers—areas where traditional event-based or differential-equation models often fall short [23–25]. Unlike discrete-event simulation (DES), which models passive queues of events over time [26], ABM captures the active, decision-making nature of agents who adapt to experiences and interactions within the healthcare environment [21]. SDM, on the other hand, is well suited for examining feedback mechanisms and longitudinal trends across the continuum of care [27–31]. It captures aggregate system changes over time—something not possible with snapshot-based methods such as DES [32]. SDM is therefore ideal for exploring resource flows, policy-level trends, and the impact of feedback structures within health systems [33]. A growing number of researchers are also employing hybrid models, which combine SDM and ABM to leverage the strengths of both while mitigating their individual limitations [27]. Hybrid models can capture both the variability of individual agents (patients, clinicians) and the emergent, system-wide dynamics of healthcare organisations. Health scientists and policymakers increasingly recognise the potential of these methods for evidence-based decision-making, ranging from emergency department optimisation [34] to health promotion and prevention policy design [35]. By simulating *"what-if"* scenarios before real-world implementation, these models offer a low-risk, cost-effective approach for testing interventions, identifying sensitive parameters, and uncovering potential spill-over effects across departments or populations [36]. Importantly, their graphical and interactive interfaces make them valuable communication tools for policymakers and stakeholders [37].The evolution of health systems modelling has been driven by advances in computational power and interdisciplinary research. Early contributions by John D. Sterman and Jay W. Forrester established SDM as a framework for analysing feedback-driven systems. Simultaneously, ABM emerged as a powerful tool through the work of Eric Bonabeau and Joshua M. Epstein, enabling the simulation of emergent phenomena.

System Dynamics Modelling (SDM)

SDM has been extensively applied to:

Healthcare policy analysis

Resource allocation

Chronic disease modelling

Studies by James B. Homer and Gary B. Hirsch demonstrated its effectiveness in modelling cardiovascular and public health systems.

Agent-Based Modelling (ABM)

ABM focuses on:

Individual behaviour

Social interactions

Disease transmission

Research by Abdulrahman M. El-Sayed and Mary Tracy highlighted its applications in epidemiology and social network analysis.

Hybrid Modelling Approaches

Recent studies emphasise integrating SDM and ABM. Work by G. A. K. van Voorn and Edward Hunter shows improved modelling accuracy through hybrid frameworks.

Applications in Policy and COVID-19

During the pandemic, modelling became critical:

Sheryl L. Chang used ABM for COVID-19 transmission

C. S. M. Currie demonstrated simulation-based decision support

Conclusion of Literature Review

SDM and ABM are complementary approaches:

SDM → macro-level policy and system trends

ABM → micro-level behaviours and interactions

Hybrid modelling represents a promising future direction.

Research Gap

Limited Hybrid Integration

Lack of standardized SDM–ABM frameworks

Data Limitations

Insufficient use of real-time and AI-driven data

Scalability Issues

ABM computational complexity vs SDM oversimplification

Policy Translation Gap

Limited real-world implementation

Geographical BiasUnderrepresentation of LMICs (e.g., India)

Validation Challenges

Lack of consistent validation techniques

Objectives

Primary Objective

Develop a hybrid SDM–ABM framework for health systems analysis

Secondary Objectives

Integrate macro and micro modelling

Evaluate healthcare policies

Improve scalability and validation

Apply models to developing country contexts

Mathematical Methodology

System Dynamics Model (SDM)

$dX(t)/dt = f(X(t), u(t), t)$

Agent-Based Model (ABM)

$S_{t+1}^{(j)} = g(S_t^{(j)}, E_t, I_t)$

Search Query Model (SQM)

$Q = H \cap A \cap M$

Screening Process (SP)

$N_1 = N_0 - N_d,$

$N_2 = f_{screen}(N_1),$

$N_3 = f_{fulltext}(N2)$

Data Representation

$Di = (Gi, Ti, Pi, Mi, Vi, Li)$

Outcome Mapping

$F: Mi \rightarrow Oi$

Validation Framework

Agreement Measure

$\kappa = [Po - Pe]/[1 - Pe]$

Sensitivity Analysis

$S = \partial O/\partial \theta$

Robustness

$R = f(N_{final}, C, V)$

Conclusions

This study demonstrates that:

SDM and ABM are essential tools for modelling healthcare complexity

Hybrid approaches provide a more comprehensive framework

There is a strong need for LMIC-focused research and real-world implementation

Future work should focus on:

AI-integrated modelling

Real-time simulation systems

Scalable hybrid frameworks

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Declarations

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Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement: The data used in this study were obtained from publicly available online sources. All relevant data supporting the findings of this study are accessible through the cited references and sources within the manuscript. No proprietary or restricted datasets were used.

Institutional Review Board (IRB) Statement: Not applicable. This study does not involve human participants, animal subjects, or any form of clinical experimentation requiring ethical approval.
Informed Consent Statement: Not applicable. The study does not involve human subjects or identifiable personal data requiring informed consent.

Ethics Statement: This manuscript does not involve any ethical concerns. The research adheres to standard academic and scientific integrity guidelines, ensuring proper citation, transparency, and responsible reporting of findings.

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