Systems-level Modelling Approaches For Complex Health Technologies: A Systematic Review

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INTRODUCTION

- Healthcare systems are **complex adaptive systems** consisting of interacting agents that act autonomously, respond to their environment, and influence one another in dynamic, often unpredictable ways.[1,2]
- Implementing **complex health** technologies requires systemic changes in care delivery, coordination, and infrastructure.
- **Traditional HTA** approaches often assume linear, isolated effects and fail to capture feedback, resource constraints, and emergent system behaviour.[3,4]
- **Systems-level modelling** (e.g., discrete event simulation, system dynamics, agents-based modelling) can represent these interactions, asses operational feasibility, and support more realistic implementation planning.

OBJECTIVE

To synthesise how **systems-level modelling** is applied to evaluate and support implementation of **complex health technologies** within healthcare delivery systems.

- We define **complex health technologies** as interventions that may be complex in their design or in their implementation, requiring adaption of existing processes for effective use (e.g., cell and gene therapies, AI-assisted diagnostics, or digital health systems)
- This review aims to:
  - Classify model types and application contexts
  - Assess complexity using the SIMULATE framework (System, Interaction, Multilevel, Understanding, Loops, Time, Emergence).[5]
  - Examine model limitations and whether models informed real-world decisions or remained conceptual.

METHOD

- Systematic searches were conducted in **Web of Science, Embase, MEDLINE (Ovid), and CINAHL (EBSCO)** covering **2000-2025**.
- The **search** strategy combined terms for: *simulation and modelling methods + health technologies and interventions + healthcare context*.
- Searches retrieved **5,542 records** after duplicates were removed.
- Screening and selection follow **PRISMA** principles using **ASReview** for semi-automated title/abstract screening.[6]
- Screening is **ongoing**: *30 studies currently included for full text*.

PRELIMINARY RESULTS

30 empirical studies included to date, screening ongoing.

Fig 1. Relationship between model type, context level, and technology domain (n=30)

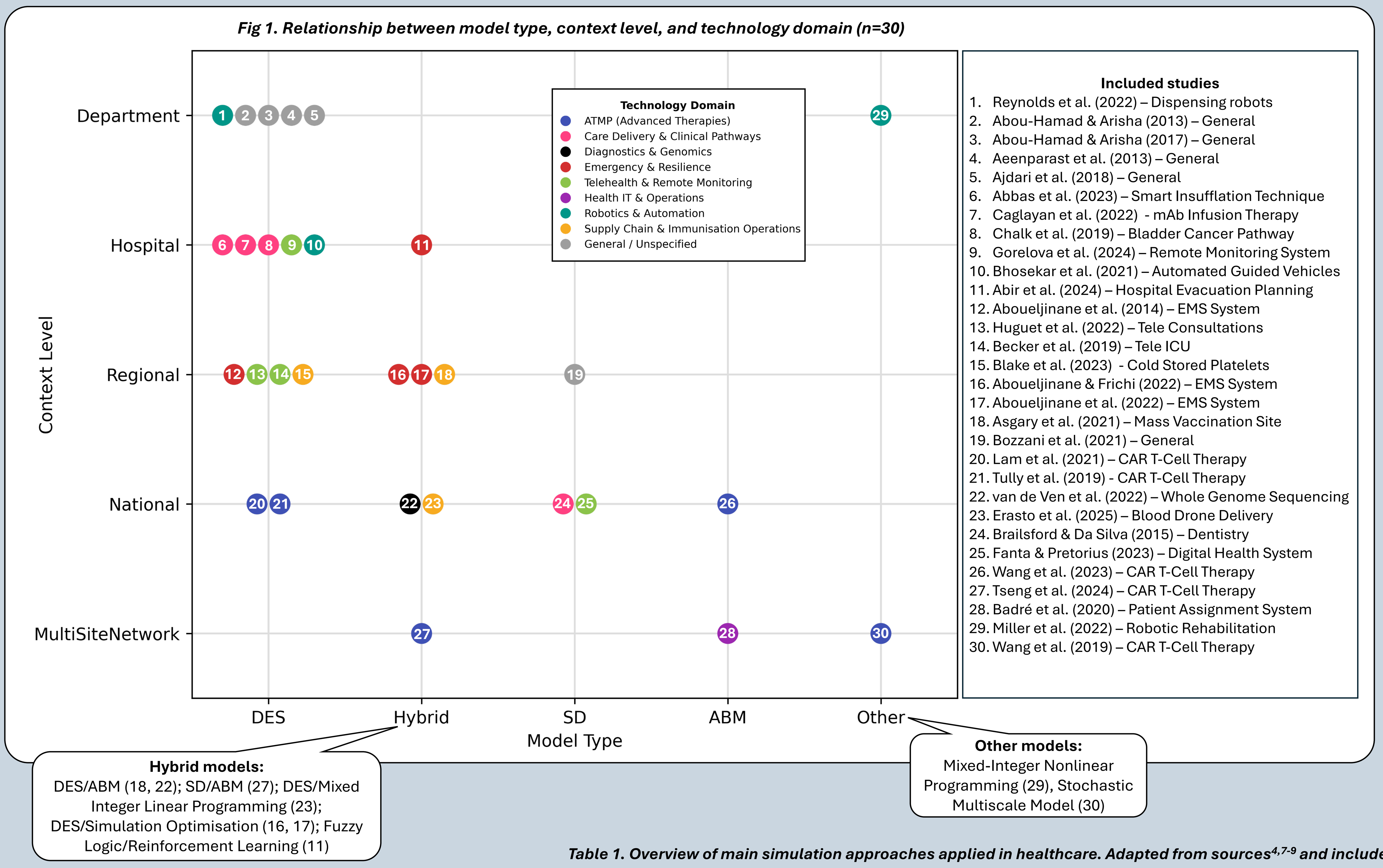

Fig 2. Level of application per model type

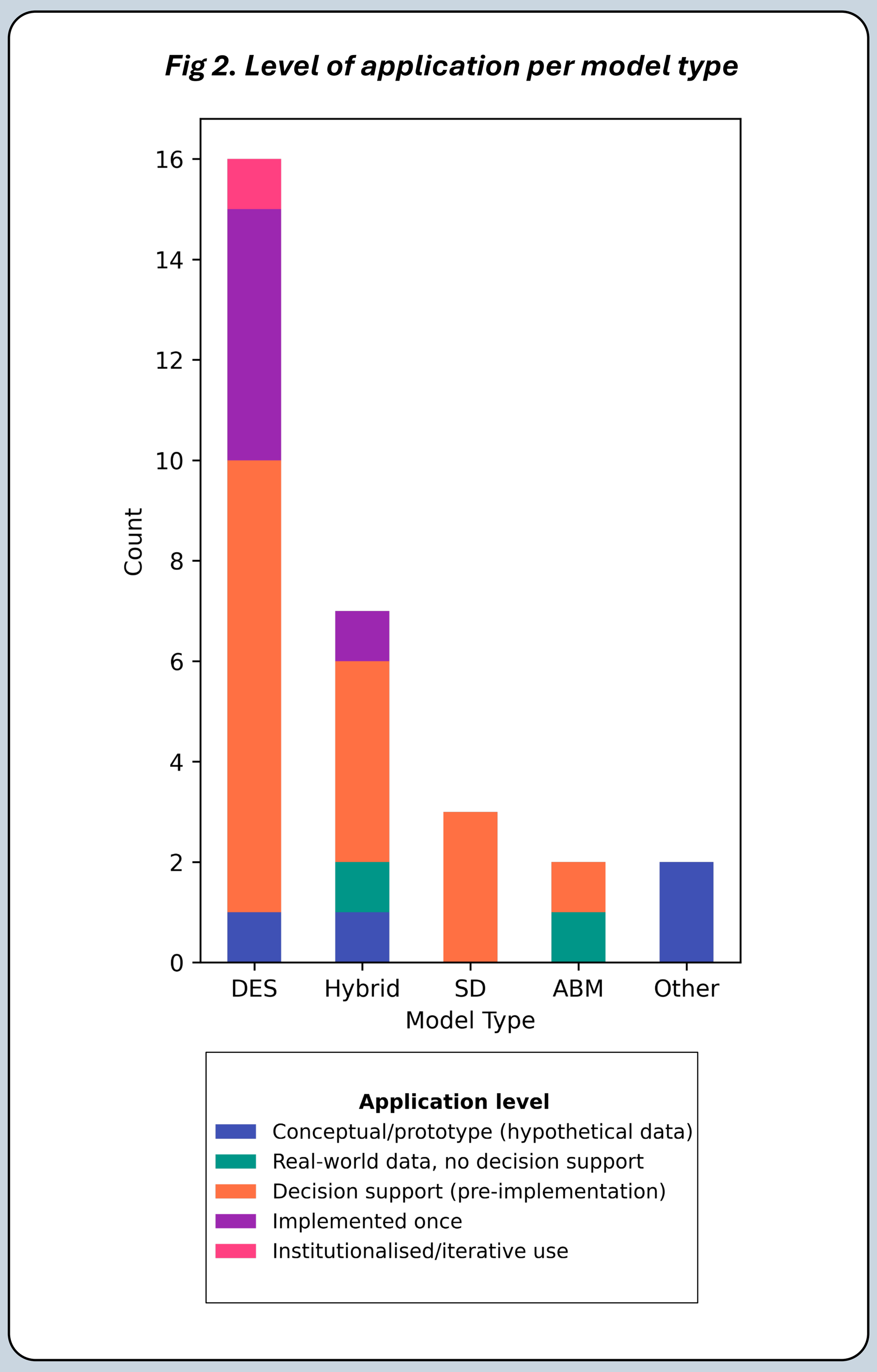

Table 1. Overview of main simulation approaches applied in healthcare. Adapted from sources[4,7-9] and included studies.

Model	Intended purpose	Advantages	Disadvantages	Example
Discrete Event Simulation (DES)	**DES** analyses individual-level processes and queues; resource use; discrete event for optimisation, prediction, and comparison.	Captures heterogeneity and time-varying attributes; good for operational and queueing problems, flexible and updatable.	Data- and time-intensive; programming and calibration can be heavy.	10 **Bhosekar et al. (2021)** developed a *DES* + optimisation framework to redesign a hospital's automated material-handling system, improving the efficiency of surgical case delivery using automated guided vehicles.
Agent Based Model (ABM)	**ABM** focuses on agents with local rules; interactions, learning, and emergent behaviours in adaptive systems.	Captures relationship networks; fits public health and infrastructure planning; handles deterministic and stochastic processes; tests behavioural responses.	Data-hungry; long build and calibration time; coding burden.	25 **Fanta & Pretorius (2023)** built an *SD* model to examine sociotechnical feedback loops in digital-health implementation, linking technology acceptance, information quality and user satisfaction in Ethiopian hospitals.
System Dynamics (SD)	**SD** analyses system-level stocks, flows, delays, and feedback; simulates behaviour over time (qualitative or quantitative).	Reveals feedbacks and emergent behaviour; suited for nonlinear, complex systems; has been used to test and compare policy and management interventions.	Limited individual-level detail; validation often qualitative if data is weak.	26 **Wang et al. (2023)** applied *ABM* within a simulation of CAR T-cell therapy logistics to represent interacting hospitals, manufacturing sites, and couriers.
Hybrid Model	**Hybrid models** combine methods when one is insufficient; integrates levels and subsystems for complex decisions.	Leverages complementary strengths; improves realism and validity; allows best-fit method per subsystem; supports learning and decision-making.	Higher model complexity; extra effort to link methods; harder verification and validation across modules.	22 **Van de Ven et al. (2022)** combined *DES and ABM* to support nationwide implementation of whole genome sequencing for lung-cancer care.

ONGOING ANALYSIS

- Full-text screening and data extraction are ongoing for remaining studies
- Comparative analysis focuses on:
  - **Complexity** of technologies: how definitions of 'complex' or 'disruptive' vary across studies.
  - **SIMULATE-coverage:** whether models address all complexity dimensions or emphasise selected elements.
  - **Model limitations:** how authors document constraints, assumptions, or validation challenges.
  - **Model evaluation:** whether hybrid models are more often implemented or updated over time.
- Findings will inform recommendations on how to model complex health technology implementation more systematically and transparently.

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