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REVIEW

Hybrid simulation in healthcare: a systematic exploration of models, applications, and emerging trends

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ABSTRACT
Hybrid Simulation (HS) refers to the utilisation of multiple simulation techniques, such as Discrete-event, Agent-based, and System Dynamics, within a single simulation study. The field of HS is expanding rapidly, with a substantial body of literature exploring its conceptualisations, frameworks, and case studies across diverse application domains. This article provides an extensive examination of the prevalence and utilisation of HS in healthcare. Through an in-depth review of fifty-seven relevant papers, we contribute to a comprehensive understanding of the current state-of-the-art in HS as applied to healthcare. The review encompasses a categorisation of modelling and simulation techniques, a thorough exploration of application types, software packages, emerging trends, potential opportunities, and challenges associated with HS in healthcare. Additionally, the review critically evaluates the limitations present in the existing literature and presents potential avenues for future research in this field.

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Hybrid simulation; discrete event simulation; system dynamics; agent-based simulation; healthcare

1. Introduction

Healthcare and social care systems are complex and multifaceted, requiring constant adaptation to changing circumstances (Giannouchos et al., 2021). The complexity of these challenges was especially evident during and continues to be apparent after the COVID-19 pandemic. As healthcare needs surged and the demands on healthcare services intensified, the intricate nature of the issues became increasingly pronounced. Furthermore, the uncertainty surrounding the pandemic's impact on healthcare outcomes further emphasised the importance of evidence-based healthcare policy and management. In order to mitigate the causes of these unplanned changes and tackle the challenges in such complex and uncertain systems, Modelling and Simulation (M&S) has proven to be a valuable method for responding to and preventing these issues (Currie et al., 2020).

M&S methods help decision-makers better understand the problem structure, creating a risk-free environment where models can be built and tested without the need for physical models or construction (Niyonkuru & Wainer, 2015). Additionally, M&S grants invaluable insight into the dynamics of complex systems, empowering modellers to gain a comprehensive understanding of system behaviour (Eldabi, 2021). This foresight allows decision-makers to make informed choices, thereby streamlining the decision-making process.

The applications of M&S in healthcare encompass a wide range of benefits, allowing for the exploration of diverse scenarios, policy development, identification of system bottlenecks, and the formulation of strategies to address these issues (S. C. Brailsford et al., 2019). Given the complexity and constant evolution of healthcare and social care systems, M&S offers a valuable tool for responding to and mitigating the causes of unplanned changes in these systems.

The analysis of M&S in healthcare literature has revealed three primary techniques employed in simulation models: Discrete Event Simulation (DES), System Dynamics (SD), and Agent-Based Simulation (ABS). Each of these techniques has unique strengths and weaknesses (Fakhimi et al., 2013; Katsaliaki & Mustafee, 2011; Palmer et al., 2018).

As previously mentioned, healthcare problems exhibit complexity across various levels, ranging from macro to micro and individual, encompassing operational and strategic aspects that necessitate interdepartmental collaboration (Eldabi, 2021). While single simulation methods are commonly employed as modelling approaches to tackle healthcare issues, their effectiveness can be hampered by the intricate nature of the problem (Mustafee et al., 2017). In such cases, employing a mixed model approach proves advantageous compared to relying solely on a single model (S. C. Brailsford et al., 2019).

Recognising the multifaceted nature of healthcare challenges, the utilisation of mixed models/Hybrid Simulation brings about several benefits. By combining different simulation techniques or incorporating complementary methodologies, mixed models enable

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a more comprehensive and nuanced understanding of complex healthcare systems. This integrated approach enhances the accuracy and reliability of the simulation results, facilitating a more robust decision-making process. Furthermore, mixed models facilitate the exploration of diverse perspectives, allowing for a holistic evaluation of healthcare problems and the identification of optimal solutions. By harnessing the strengths of multiple models, healthcare practitioners can effectively address the complexities inherent in healthcare and derive valuable insights to inform policy-making and operational improvements.

Lately, there has been a growing interest in Hybrid Simulation (HS) as a potential solution for addressing complex challenges in various fields, including healthcare (Mustafee et al., 2017). Commercial software such as Simul8, Vensim, and AnyLogic are generally employed to construct HS models in practice (Eldabi et al., 2018). Despite this, developing HS models for healthcare purposes can be challenging due to the multiple coding environments and skills required, indicating that additional research is necessary.

HS has gained considerable attention from researchers in the past two decades, with various studies focusing on different combinations of models. For instance, Lättilä et al. (2010) explore when and why HS is appropriate and how it can be developed and analysed. They also provide insights into the development of HS models, utilising the strengths of both ABS and SD to achieve a comprehensive, realistic understanding of complex systems, thereby aiding in more effective decision-making and policy development. Tako et al. (2019) suggest that hybrid models should be conceived at the beginning of the simulation life cycle, either during problem formulation or at the conceptual modelling stage. This approach is recommended to avoid unnecessary complexity and wasted efforts, hence, the decision to adopt HS should be based on solid reasoning. Another panel paper by Eldabi et al. (2016) explores HS, discussing its roots, current challenges, and future potential. Their paper posits that HS offers enhanced insights into real-life systems as it enables modellers to examine inherent problems from diverse dimensions. It proposes a structured approach to HS comprising five main components: selection and identification, conceptual hybridisation and development, verification and validation, experimentation and running, and expertise. The paper concludes by advocating for continued research to further clarify, refine, and expand the ontological basis of HS through both taxonomy and a system of definitions.

With the increasing popularity of HS, periodic literature reviews are necessary to observe advancements in the field. A notable literature review study conducted by S. C. Brailsford et al. (2019) provided a systematic literature review on HS, as well as a framework for the stages of HS. They suggest analysing the stage of the life cycle of simulation to develop HS. Their review did not exclusively focus on healthcare-specific problems, as it encompassed various disciplines such as supply chain management, manufacturing, and healthcare. Dos Santos et al. (2020) conducted a review exclusively focused on HS applications in healthcare, primarily examining application papers within this domain. Theoretical and methodological papers were excluded from their review. Since these reviews were conducted, there has been a significant increase in the number of papers published on HS in healthcare. The application of HS in healthcare has grown rapidly, possibly owing to the recognition of the methodology's advantages and the increasing capabilities of software packages and data analytics methodologies. Consequently, conducting a comprehensive literature review on HS in healthcare is necessary to (1) investigate existing HS frameworks, (2) explore methods of combining models, (3) identify preferred software in the healthcare domain, and (4) identify any potential gaps in the literature and suggest avenues for further research in developing HS models for healthcare systems.

The rest of the paper is organised as follows: Section 2 discusses the three most applied M&S methods and their associated limitations. Section 3 presents the search methodology and systematic analysis of the literature. Section 4 presents the results of the analysis of the papers in the literature review. Section 5 discusses the papers in general and identifies gaps in the literature. Finally, Section 6 concludes the paper and offers suggestions for future research.

2. Research background

This section aims to offer a thorough exploration of how HS is utilised in healthcare, highlighting its diverse applications. Moreover, we will delve into specific areas where DES, SD and ABS find their relevance within the healthcare context. To enrich our discussion, relevant examples will be incorporated. This section will also address the challenges associated with relying solely on stand-alone simulation models. By doing so, we aim to provide a concise overview of the advantages and potential of HS in healthcare.

2.1. Simulation in healthcare

M&S techniques are essential for improving healthcare systems, lowering costs, and developing realistic representations of healthcare systems (S. C. Brailsford, 2007; Landa et al., 2018). Gunal (2012) describes how DES is routinely used to predict patient flow, resource allocation, and healthcare services. It improves patient admission and staff scheduling by optimising resource allocation, staffing, and equipment (Harper et al., 2017;

Table 1. The limitation of M&S methods used for healthcare problems.

M&S Approach	Limitation	Sample studies
DES	• Complicated to represent social behaviour. • Require a significant amount of data. • Mostly capture detailed complexity.	S. Brailsford and Schmidt (2003), Jacobson et al. (2013), Chahal et al. (2013)
SD	• Not suitable for a detailed perspective. • Mostly capture dynamic complexity. • Mainly deal with macro-level problems.	Viana et al. (2014), Eldabi (2021), S. C. Brailsford et al. (2010)
ABS	• Individual-level perspective. • Involves high skills in computation. • Difficult to process visually.	Barnes et al. (2013), Eldabi (2021), Joo et al. (2013)

Vasilakis et al., 2007). SD is widely used in healthcare research, allowing for policy formulation, disease epidemiological analysis, and healthcare capacity (Homer & Hirsch, 2006). It has been used to treat a variety of health issues, including obesity, HIV, tuberculosis, diabetes, and cancer (Abdel-Hamid, 2002; Frerichs et al., 2013; Jalali et al., 2014; Miller et al., 2011; Sugiyama et al., 2017). SD can also be used to improve hospital operations and system design (Cooke et al., 2010). ABS is commonly used to evaluate staffing, economics, patient safety, and disease outbreaks (Jones & Evans, 2008; Miksch et al., 2019). ABS can help researchers understand disease transmission pathways, human behaviour, and interactions within the healthcare system (Stephenson et al., 2020). ABS is particularly beneficial in healthcare for evaluating human behaviours (Siebers et al., 2010).

2.2. Challenges of simulation in healthcare

Healthcare problems are complex and interconnected, involving various departments and even macro and micro-level issues, such as operational and strategic levels. While simulation models have their strengths in addressing healthcare problems, many complex issues necessitate the use of additional tools to overcome their complexity (Eldabi, 2021). Relying solely on a single simulation model is insufficient to tackle the intricacies of these problems. While a single model may effectively explain the problem, constructing the model itself can be too intricate to comprehend. Therefore, different simulation methods are necessary when dealing with complex problems.

For instance, DES can capture detailed complexity but may not offer a solution to problems with dynamic complexity. Additionally, the DES model might be too simplistic to represent real-world problems, overly complex for decision-makers to understand, or lack the flexibility to accommodate changes in larger problems (Chahal & Eldabi, 2011). On the other hand, SD can capture dynamic complexity and provide solutions for complex healthcare problems from a macroscopic perspective. However, decision-makers also need to comprehend the individual and detailed aspects of healthcare problems, as the patient flow or attributes are crucial for a comprehensive and realistic understanding. As a result, relying solely on standalone SD modelling may not be enough to tackle the complexity of healthcare systems. This is because it has limitations when it comes to representing detailed aspects (Tako & Robinson, 2009). To address both structural and detailed complexity, DES components are also necessary for modelling healthcare systems. Finally, to capture emergent complexity, ABS is a valuable method that employs a bottom-up approach and provides insights into the system's components (Sumari et al., 2013). Therefore, relying solely on standalone simulation methods may not yield optimal solutions for complex healthcare problems, as such problems necessitate addressing dynamic, detailed, and emergent complexity simultaneously (Mustafee et al., 2015).

In order to overcome the complexities mentioned in Table 1, using HS is one of the effective ways since it can cover micro, macro, and individual aspects of healthcare problems (Eldabi et al., 2016). In addition, HS enables stakeholders to understand the simulation process and supports decision-making by presenting the problem in a straightforward manner. Partial analysis of healthcare systems is impractical due to the interdependencies among their components, making it impossible to isolate individual parts. Therefore, HS models to offer more comprehensive and efficient solutions, providing a clearer representation of complex healthcare systems (S. C. Brailsford et al., 2013a).

3. Literature review framework and search methodology

The systematic literature review (SLR) was initiated by determining the databases and keywords to be utilised. For this review, the authors selected well-known databases, namely Web of Science and Scopus. To ensure comprehensive coverage, relevant keywords were carefully chosen based on the scope of the literature review.

The first group of keywords centred around HS, aiming to capture papers specifically related to this area of research. These keywords were specifically generated to identify studies focused on hybrid simulation. The second group of keywords involved combinations of SD, DES, and ABS, enabling the detection of papers that incorporated these simulation methods in combination. The final group of keywords targeted healthcare-specific papers, ensuring a focused approach for the literature review.

The preliminary results of this literature review were previously presented in Kar et al. (2022), providing an initial glimpse into the findings. To maintain a healthcare-focused approach and to capture all relevant papers in the field, additional healthcare-related keywords were carefully incorporated into the SLR. These additional keywords helped to refine the search and ensure that healthcare-specific papers were included in the review. The complete list of keywords used in the SLR is presented in Table 2.

To ensure a systematic review of the current literature, a four-phase approach, as depicted in Figure 1, was followed to identify, screen, and include relevant articles. Initially, a total of 5,665 articles were identified based on the keywords used in Scopus and Web of Science. Subsequently, 662 articles were eliminated as they were duplicates or inaccessible online. Additionally, articles that were unrelated to the research objectives, either due to using different methodologies or not being focused on healthcare, were excluded during the screening process.

After the screening process, 220 articles specifically related to HS in healthcare were identified. However,

Table 2. Literature search for hybrid simulation in healthcare.

Category	Search Terms
Hybrid Simulation	("Hybrid Simulation")
	OR
Combined Simulations	[("Discrete Event Simulation" AND "System Dynamics")
	OR ("Discrete Event Simulation" AND "System Dynamics" AND "Agent-Based Simulation")
	OR ("Discrete Event Simulation" AND "Agent Based Simulation")
	OR ("Agent-Based Simulation" AND "System Dynamics")]
Healthcare	AND ("Healthcare" OR "Disease" OR "Medic*")

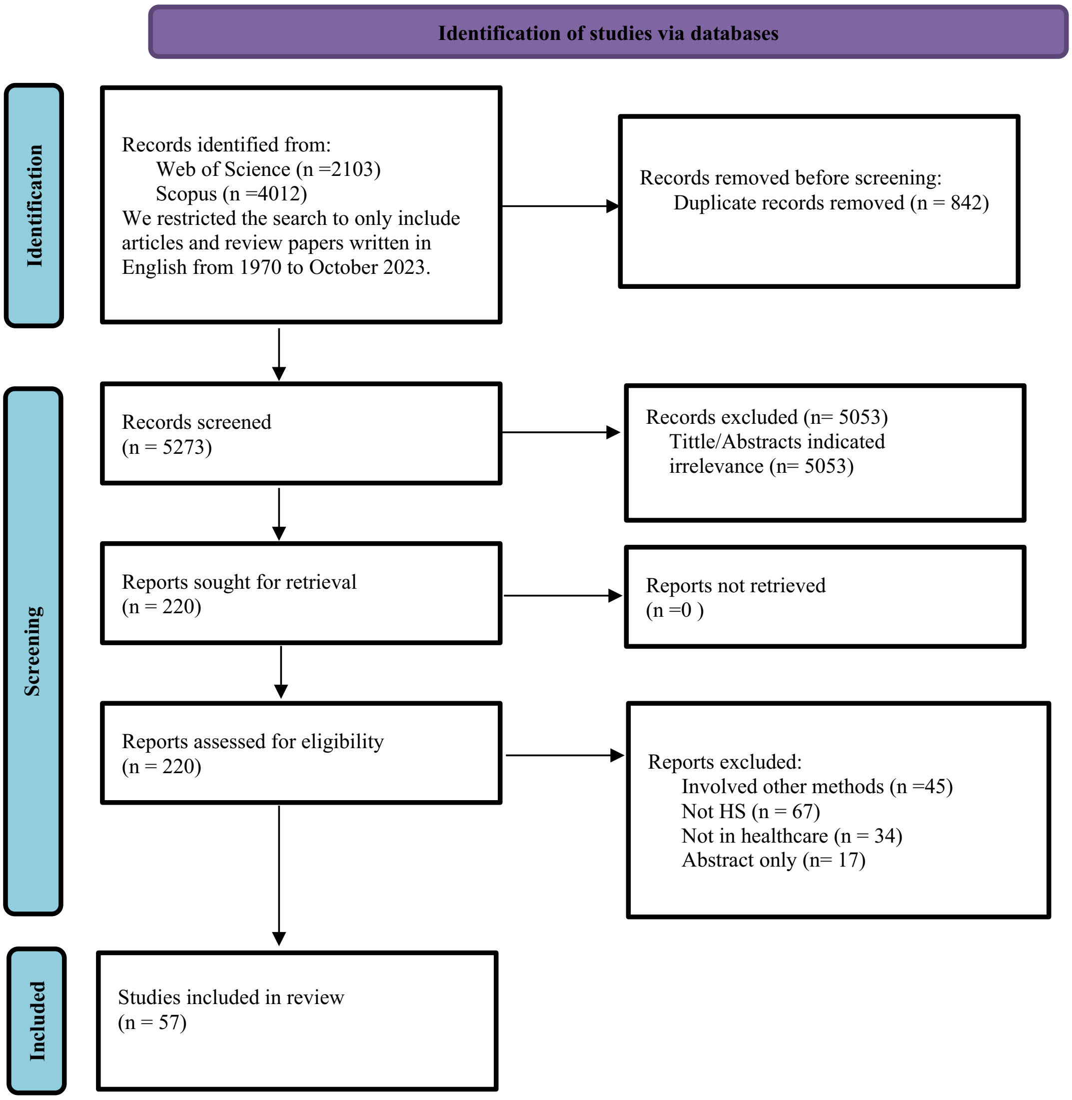

Figure 1. Phases of systematic literature review.

some of these articles utilised modelling approaches other than DES, SD, and ABS, and thus were removed from the SLR. Ultimately, 57 articles that employed any combination of DES, SD, and ABS within the context of healthcare were included in this SLR.

It's worth mentioning that the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines were utilised to ensure the rigour and transparency of the SLR process. Following these guidelines contributes to the methodological robustness of the review and enhances the reliability of the findings. The process of selecting articles from the target databases consists of four phases, as outlined below:

- Phase 1 (Analysis Unit): This phase involves determining the type of papers to be analysed, such as peer-reviewed articles, articles, or conference papers. Additionally, the search engines Web of Science and Scopus were utilised.
- Phase 2 (Definition and Categorisation of Context): In this phase, the scope of the literature review is defined, specifically focusing on hybrid simulation in healthcare. The review will include only DES, ABS, and SD approaches.
- Phase 3 (Retrieval and Delimitation of Articles): A three-stage screening procedure was implemented in this phase, which includes screening based on title, keywords, year, and abstract. Overlapping articles were detected and eliminated as part of the process.
- Phase 4 (Analysis of Collected Articles): In the final phase, the collected articles were thoroughly analysed to investigate their methodology, findings, and challenges.

Database of this literate review is presented at the end of this document. The data reveals that a total of 57 papers have been carefully collected and thoroughly analysed. These papers encompass a variety of categories, including frameworks, applications, and literature review papers. A comprehensive and detailed explanation of each paper is provided in Section 4 of this report.

4. Findings

This literature review is built upon the framework presented by Mustafee et al. (2021). The selected literature has been thoroughly examined and organised into four key sections: Profiling Research (P), Problem Definition and Context (P), Model Development and Implementation (M), and Study Outcome (O). Table 3 summarises the framework.

Section Section 4.1 presents the Profiling Research (P) results obtained from the SLR. This part provides a comprehensive overview of the existing literature, identifying key trends and patterns in the application of HS within healthcare settings. In Section 4.2, the focus shifts to Problem Definition and Context (P) concerning HS in healthcare studies. This section delves into HS motivations and contexts within healthcare that HS aims to address. Section 4.3 discusses all aspects of Model Development and Implementation (M). It covers the various applications and frameworks of HS that are used to tackle healthcare challenges, demonstrating the adaptability and technical approaches of HS in this field. Lastly, Section 4.4, titled Study Outcome (O), explores the actual implementation of HS and future research directions in this area.

4.1. Profiling Research (P)

In the Profiling Research (P) stage of the literature review, papers are categorised based on attributes such as their year of publication and type. An overview of the publication years will be offered, along with a breakdown of publication types, encompassing journal articles, conference papers, and book chapters, complete with corresponding percentages. General statistics depicting the proportions of different paper types, including review, application, and framework papers, will also be presented.

The dataset of our review comprises 57 publications that span from 2008 to 2023. Notably, there was a relatively low number of articles before 2012, with only four publications during that period. However, starting from 2012, there has been an upward trend in the publication of HS in healthcare-related articles. Specifically, six articles were published in 2013, seven articles in 2014 and 2016, and 26 articles between 2017 and 2023.

Table 3. PPMO framework (adapted from Mustafee et al. (2021)).

(A) Profiling Research (P) • Publication characteristics (publication year, publication type etc.) • Type of paper (literature review paper, application paper, framework)	**(B) Problem Definition and Context (P)** • The motivation of hybridisation • Context of application • Case study
(C) Model Development and Implementation (M) • A hybrid approach/combination • M&S software and other tools • Linking approaches • The way of model connections • Verification and validation	**(D) Study Outcome (O)** • Level of implementation • Future research direction

One finding was that the majority of the publications (35 out of 57) were in conference format, while the remaining 21 were Journal papers. This aligns with the findings of a previous review on HS by S. C. Brailsford et al. (2019) which indicated that more than half of the articles were published in conference proceedings. However, among papers published post-2018, 71% were journal articles. In addition, our findings show that 49 out of 57 papers reviewed for this study were application papers (Ahmad et al., 2014; Fakhimi et al., 2014; Li, Zhang, Chi, et al., 2020) 5 presented frameworks (Chahal & Eldabi, 2008; Zulkepli & Eldabi, 2016) and applications, and 2 were literature reviews (Dos Santos et al., 2020; Nguyen et al., 2020).

Figure 2 provides a visual representation of the findings, demonstrating the distribution of M&S combinations used in the identified papers. Notably, approximately 42% of the papers (23 papers) utilised a combination of SD-DES. However, in more recent papers, the combination of DES-ABS (Elliott et al., 2019; Viana et al., 2020) or SD-ABS (D. C. Evenden et al., 2021; Nguyen et al., 2022) gained more prominence. On the other hand, the combination of all three simulation methods (DES, SD, and ABS) (Gao et al., 2014) received less attention from researchers compared to the other combinations.

4.2. Problem Definition and Context (P)

In this section, we explore the motivations for hybridisation, the contexts in which it is applied, and the case studies that have been conducted. This information is expected to be helpful for researchers seeking a comprehensive understanding of the landscape of HS literature within healthcare. The focus is on the underlying motivations for employing hybridisation. Various application contexts, including disease management, emergency department operations, outpatient clinics, and others, are examined alongside relevant case studies.

4.2.1. The motivation of Hybridisation

Based on the analysis of the papers, 5 main categories are defined. Table 4 provides the categories and sample studies that motivated HS.

Our database indicates that 33% of application papers develop HS to enhance or assist decision-making processes, making it one of the most common motivations in healthcare. Another significant driver, accounting for 24% of the cases, is increased accuracy. This is primarily because single simulation models may not fully address healthcare-related questions, and combining different modelling approaches can yield more precise results. Policy/Scenario testing, constituting 20% of the applications, benefits from HS's ability to capture system details while assessing policy impacts. 16% of the paper developed HS in order to have a broad representation of the system. Finally, the focus on model reusability is still infancy. Only 7% of the applications had motivations for reusability.

4.2.2. Context of HS and Case Studies

Our database shows a broad range of applications for Hybrid Simulation (HS) in healthcare systems, extending from ambulance services to social care. The literature categorises the contexts of HS based on specific criteria. A substantial portion of the papers focuses on applying HS within hospital/clinic services (23%) and emergency departments (21%), indicating these areas as primary centres of healthcare challenges.

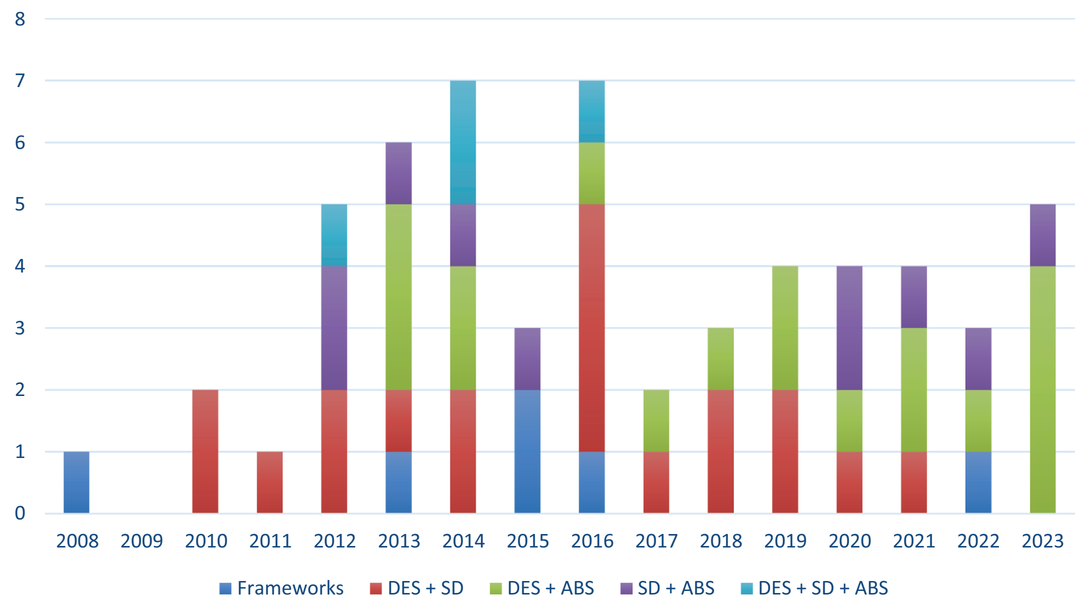

Figure 2. A synopsis of HS literature in healthcare.

Table 4. The motivation of Hybridisation.

Motivation	Description	Example Studies
Broad Representation/ Complex System Representation	Interconnectivity is a primary driver for using HS, as it allows for a more comprehensive representation of the system rather than focusing on isolated parts.	Ahmad et al. (2014), Bell et al. (2016), Djanatliev and Meier (2016), Viana et al. (2012)
Improve Decision Making	A significant utility of simulation is its role in enhancing decision-making processes. HS improve decision-making capabilities, making it a key motivation for its application.	Nouman et al. (2013), Zulkepli and Eldabi (2016), Mielczarek and Zabawa (2018), Li, Zhang, Chi, et al. (2020), Zhou et al. (2023)
Increase Accuracy	HS can potentially offer greater modelling accuracy when compared to singular simulation methods. This enhancement in accuracy is a notable reason for the application of HS.	Lassnig et al. (2019), Elliott et al. (2019), D. Evenden et al. (2020), Hamza et al. (2021)
Innovation/ Policy Testing	HS, with its capacity to integrate both holistic and detailed views of systems, offers improved insights into policy design. This makes policy testing a significant motivator for HS use.	Djanatliev and German (2013), Kolominsky-Rabas et al. (2015), Day et al. (2014)
Reusability	The ability to reuse system components is increasingly valued, especially given the time-intensive nature of developing HS models from scratch. Some studies have focused on demonstrating how HS can facilitate reusability	Anagnostou and Taylor (2014), Lather and Eldabi (2020)

Additionally, healthcare service management emerges as a frequently addressed context, with approximately 16% of studies concentrating on this aspect. Following the COVID-19 pandemic, there has been a marked increase in studies related to disease management, accounting for 14%. Ambulance services also receive notable attention, with 10% of papers focusing on this area. Notably, only a small fraction (4%) of the papers delve into policy design in healthcare, highlighting a potential area for future research. The remaining papers explore social care, health economy, and hospital processes.

An analysis of the geographical distribution of these studies shows that the majority were conducted in the UK, particularly within the hospital/clinic context. Case studies in this area include outpatient clinics, orthopaedic clinics, cancer centres, and eye units. The emergency department context primarily focuses on resource allocation and scheduling. In contrast, healthcare service management in Poland concentrates on bed capacity and hospital demand analysis. Disease management studies have predominantly centred around COVID-19 related issues.

4.3. Model Development and Implementation (M)

The Model Development and Implementation (M) stage entails a comprehensive analysis of the methods employed, examining combinations of methods, the software used, and approaches to integration/linking, along with verification and validation processes. This analysis is based on the method combinations outlined in the reviewed papers, such as DES-SD, DES-ABS, and SD-ABS. The discussion also covers the software utilised and explores model linking methods, following J. S. Morgan et al. (2017) framework, which includes enrichment, integration, interaction, and sequential linking. Additionally, the way of model connection is categorised into three types: manual linking, where one model's output is manually copied and pasted into another; intermediate tool linking, using tools like Excel; and automated linking, performed by the software itself (S. C. Brailsford et al., 2019).

The model validation process is analysed through various methods, including statistical analysis, face validity, or external validity (S. C. Brailsford et al., 2019). Standard statistical methods, such as regression, sensitivity analysis, and data comparison, are employed for validation. Face validity is used when data availability is limited and typically involves assessments by domain experts and stakeholders. External validity, on the other hand, assesses the generalisability of the model to real-world healthcare contexts.

4.3.1. Hybrid simulation frameworks in healthcare

In the healthcare domain, HS gained researchers' attention more than a decade ago. Our analysis reveals the existence of five notable HS frameworks specifically developed for healthcare applications (Table 5.) Among these frameworks, one of the early contributions in this field was made by Chahal and Eldabi (2008). Their framework presents a structured approach to combining SD and DES to address complex healthcare problems. It offers three distinct formats for integrating SD and DES models, each tailored to tackle different levels of complexity.

The framework proposes three formats for model combination between DES and SD: hierarchical format (SD representing the strategic level and providing information to the DES model representing the operational/tactical level), process-environment format (DES is designed to represent the process while SD captures the surrounding environment), and integration (making the system function as a whole without easily distinguishing between the DES and SD components). In subsequent work, Chahal et al. (2013) proposed cyclical and parallel interaction formats for their HS Framework. The parallel interaction format allows models to communicate during runtime, while the

Table 5. HS frameworks in healthcare.

Authors	Contribution	Framework Components	Used Methods
Chahal and Eldabi (2008)	It proposed three-way of model a combination	Hierarchical Mode Process-Environment Mode Integration	DES-SD
Chahal et al. (2013)	It improved the previous framework by defining the information flow	Parallel Interaction Cyclic Interaction	DES-SD
Zulkepli and Eldabi (2015)	It is a guiding framework for the conceptual phase	Conceptual Phase Modelling Phase Model Communication Phase	DES-SD
Fakhimi (2016)	It considers sustainability factors for complex healthcare modelling.	Conceptual Phase Design and Combination Phase TBL Analysis Phase	DES-SD
Djanatliev and German (2015)	It introduces domain-specific HS.	Level Identification Horizontal Paradigm Linking Vertical Paradigm Linking	DES-SD-ABS

cyclical interaction format enables interaction between the models after the run.

Zulkepli and Eldabi (2015) proposed a guiding framework for HS at the conceptual phase for non-modellers. The difference between this framework and Chahal et al. (2013) is to show the necessity of HS in the early stage. In order to improve the previously explained framework, it used some components from Helal et al. (2007) paper. This framework is developed only for DES and SD, therefore, conceptual explanation for other combinations needs to have further analysis.

Fakhimi (2016) contributed to the field of HS in healthcare by developing a framework that incorporates a sustainability perspective. The framework takes into account the concept of triple bottom lines (TBL) while addressing the complexity of modelling in healthcare. To achieve this, Fakhimi suggests combining two modelling approaches: Discrete and continuous. Fakhimi's framework provides a valuable contribution to the field by emphasising the importance of considering sustainability factors in healthcare modelling. By integrating DES and SD and incorporating TBL principles, the framework offers a structured approach for incorporating sustainability metrics into the modelling process.

Djanatliev and German (2015) propose an HS framework for analysing healthcare systems. Their framework includes three main phases: identifying appropriate levels of abstraction or subclasses, horizontal paradigm linking, and vertical paradigm linking. The study demonstrates that domain-specific HS approaches can effectively address the necessity of developing HS models. When a problem involves multiple levels, HS becomes essential. The horizontal paradigm linking involves mapping simulation methods and assigning them to the correct level within the specific healthcare domain. On the other hand, the vertical paradigm linking focuses on facilitating data interaction between the simulation models. While this framework shares similarities with other existing frameworks, what distinguishes it is the inclusion of ABS in the combination of models. By incorporating ABS into the vertical and horizontal linking process, this framework offers a unique approach to integrating different simulation methods for healthcare applications. This expanded perspective allows for a more comprehensive and nuanced understanding of complex healthcare systems.

4.3.2. Hybrid simulation applications in healthcare

In this section, we will explore the application papers that implement HS in a case study specifically focusing on HS in healthcare. These papers are categorised into four distinct combinations: DES-SD, DES-ABS, SD-ABS, and DES-SD-ABS. Each paper within these subsections will undergo a comprehensive analysis based on the criteria outlined in Table 3 section model development and implementation (M).

According to S. C. Brailsford et al. (2019) sequential, is where two models are executed consecutively, with the output of one model serving as the input for the other. Enriching technique involves incorporating limited elements from one method into a primary method (it is similar to the Process-environment mode in Chahal and Eldabi (2008)). In the interaction technique, two separate sub-models interact, functioning as a cohesive whole (it is similar to the Hierarchical mode in Chahal and Eldabi (2008)). Lastly, the integration technique lacks a clear demarcation between models, with a seamless transition from one to another. The linking process can be classified into three types: manual linking, where output is manually copied and pasted between models; the intermediate tool approach, which uses external tools like Excel to link models; and automated linking, where the software enables model communication.

This analysis will delve into the methodology, findings, and challenges addressed in each paper, providing valuable insights into the practical applications of HS in the healthcare domain.

4.3.2.1. Combination of DES-SD. The early stages of exploring the combination of DES and SD have yielded several papers introducing the potential benefits and methods of integrating these models. Chahal and Eldabi (2010) conducted a comparative study that examined the strengths of SD and DES from three perspectives: system perspective, problem perspective, and a methodology perspective. Their findings shed light on the unique advantages offered by each method. Additionally, J. Morgan et al. (2011) employed SD to analyse the dynamics of government targets in relation to R&D adoption, while DES was used to assess the day-to-day impact of changing treatment regimes. These studies demonstrated the distinct capabilities of both models and emphasised the potential contributions that can be achieved through their combination.

In a pioneering study on the fusion of DES and SD, S. C. Brailsford et al. (2010) aimed to assess the practical utility of HS. Their objective was to identify the circumstances in which HS proves beneficial. While their work did not yield a fully integrated model, it provided valuable insights and paved the way for exploring the advantages of combining DES and SD at the strategic and operational levels. Expanding on this research, Viana et al. (2014) extended the study by linking SD and DES methods to predict clinic performance for Chlamydia and model the community infection process. The results demonstrated that the combined approach outperformed the individual methods. Notably, an enrichment format using automated interaction in Excel was preferred for facilitating the integration between the models.

The study of Emergency Departments (ED) has been significantly advanced by incorporating HS models, especially the integration of DES and SD. Ahmad et al. (2012, pp. 2013, 2014) led this approach with a series of papers focusing on HS models for EDs. Their work highlighted the benefits of DES and SD integration in addressing complex dynamics in EDs, although it lacked a comprehensive evaluation of the validation process.

Additionally, Bell et al. (2016) explored a whole-system modelling approach using SD-DES in healthcare. They focused on a comprehensive HS project for non-elective health services, introducing software design methods for requirements gathering, model design, and data flow integration. While their study did not delve deeply into model development specifics, it underscored the importance of HS, especially in A&E departments.

Mielczarek and Zabawa (2016) conducted a case study using a Hybrid SD-DES model to examine the long-term effects of population changes on healthcare demand in the Wroclaw region of Poland. They later expanded this model (Mielczarek & Zabawa, 2021) to estimate healthcare service demand, using DES for emergency demand generation and SD for demographic prediction. The sequential HS model proved effective for future hospital service demand forecasting, capturing individual-level data in DES and aggregated data in SD. Their work's relevance was further expanded in later studies (Mielczarek & Zabawa, 2017, 2018; Mielczarek et al., 2018; Zabawa & Mielczarek, 2019) exploring the model's applicability at both local and national levels.

Mielczarek (2019). further extended this research, utilising ExtendSim/Arena for modelling the impact of demographic changes on hospital inpatient services demand. This study adopted an HS approach with SD building the population model and DES depicting patient paths, using Excel for sequential model integration and statistical methods for validation. The integration here was primarily one-way, from the SD to the DES component.

Zulkepli and Eldabi (2016) improved upon their previous work (Zulkepli et al., 2012). by developing an integrated care system model combining SD and DES. This work developed three distinct models: one for hospital-level, one for intermediate care (using DES), and one for social care (using SD), thereby enhancing the decision-making process.

Furthermore, J. S. Morgan et al. (2016) studied the potential advantages of a mixed-method approach for stakeholders and modellers, using SD for macro-level analysis and DES for individual-level problem-solving. Their findings supported the feasibility of conceptualising mixed models to address complex issues. Finally, in a different approach, Lather and Eldabi (2020) present an innovative method for developing rapid HS models as needed. Their study highlights the practicality of constructing HS model by leveraging pre-existing single-approach models available in the public domain. The authors propose the establishment of a modelling hub that allows for the integration of diverse models from different backgrounds and localities, resulting in a more comprehensive modelling response during pandemics. To facilitate this integration, they devised a mapping technique that establishes connections between variables in different models, enabling effective communication and interaction. Model integration was achieved using the enrichment method, with manual linking conducted via Excel for combining the models. The development of the models involved the utilisation of both Vensim and AnyLogic.

The studies discussed above collectively highlight the prominence of combining DES and SD as one of the most preferred model combinations in HS. Table 6 provides a summary of the information regarding this combination.

4.3.2.2. Combination of DES-ABS. Initially, the combination of DES and ABS did not receive as much attention from researchers compared to other HS approaches. However, S. C. Brailsford et al. (2013a) conducted a study investigating the combination of DES and ABS for age-related macular degeneration in the UK (see Table 7). They developed their model using the AnyLogic platform and found that reusable model development in AnyLogic posed challenges and required advanced coding skills.

Table 6. Combination of DES and SD Application[1].

Studies	Method	Linking	Validate/Verify	Software
J. Morgan et al. (2011)	Sequential	NA	NA	Vensim/Simul8
S. C. Brailsford et al. (2010)	Enriching	Intermediate Tool	FV/SM	Vensim/Simul8
Viana et al. (2014)	Interaction	Intermediate Tool	SM	Vensim/Simul8
Ahmad et al. (2012)	Interaction	Automated	FV	AnyLogic
Ahmad et al. (2013)	Interaction	Automated	FV	AnyLogic
Ahmad et al. (2014)	Interaction	Automated	FV	AnyLogic
Bell et al. (2016)	Interaction	NA	NA	WSP/Simul8
Mielczarek and Zabawa (2016)	Interaction	NA	SM	ExtendSim
Mielczarek and Zabawa (2021)	Sequential	NA	SM	ExtendSim/Arena
Mielczarek and Zabawa (2017)	NA	NA	NA	ExtendSim/Arena
Mielczarek and Zabawa (2018)	NA	NA	NA	ExtendSim/Arena
Mielczarek et al. (2018)	Sequential	NA	NA	ExtendSim/Arena
Zabawa and Mielczarek (2019)	Sequential	NA	SM	ExtendSim
Mielczarek (2019)	Sequential	Intermediate Tool	SM	ExtendSim/Arena
Zulkepli et al. (2012)	Interaction	Manual	NA	Vensim/Simul8
Zulkepli and Eldabi (2016)	Interaction	Manual	SM	Vensim/Simul8
J. S. Morgan et al. (2016)	Sequential	NA	NA	NA
Lather and Eldabi (2020)	NA	Manual	NA	Vensim/Simul8

[a]NA: Not Available or Not Mentioned, FV: Face Validity, SM: Statistical Method EV: External Validity.

Table 7. Combination of DES and ABS.

Studies	Method	Linking	Validate/Verify	Software
S. C. Brailsford et al. (2013a)	Interaction	Automated	FV	AnyLogic
Anagnostou et al. (2013)	Interaction	Automated	NA	Repast Simphony/poRTIco
Nouman et al. (2013)	Integration	Automated	NA	Repast Simphony/poRTIco
Day et al. (2014)	Interaction	Automated	SM	AnyLogic
Fakhimi et al. (2014)	Sequential	Intermediate Tool	NA	Repast/Simul8
Kittipittayakorn and Ying (2016)	Enriching	Automated	SM	AnyLogic
Li, Zhang, Chi, et al. (2020)	NA	Automated	SM	AnyLogic
Hamza et al. (2021)	Interaction	Automated	SM	AnyLogic
Elliott et al. (2019)	Enriching	Automated	SM	AnyLogic
Viana et al. (2017)	NA	Automated	NA	AnyLogic
Viana et al. (2018)	Interaction	Automated	SM-FV	AnyLogic
Viana et al. (2020)	NA	Automated	FV	AnyLogic
Lassnig et al. (2019)	NA	Automated	SM	AnyLogic
Angelopoulou and Mykoniatis (2022)	NA	Automated	SM	AnyLogic
Anagnostou et al. (2022)	Sequential	N/A	N/A	Python-Simpy
Zhou et al. (2023)	N/A	Automated	SM	AnyLogic
Penny et al. (2023)	Enriching	Automated	SM	Simul8
Liu et al. (2023)	Enriching	Automated	N/A	AnyLogic

In addition, studies on distributed simulation have explored the integration of DES and ABS. For instance, the Repast Symphony platform was employed to develop two distinct models: an Ambulance Service Model in ABS and an A&E Model using DES. These models were then integrated into a distributed hierarchical simulation, enabling time synchronisation and communication between them. The aim of the simulation was to investigate Emergency Medical Services, specifically focusing on the interactions between the ambulance service and the A&E service in London, UK. The simulation utilised the poRTIco RTI software for execution (Anagnostou et al., 2013; Nouman et al., 2013). The authors argued that including ambulance services in the model was crucial for a more accurate representation of the A&E department, as it cannot be adequately modelled without considering ambulance services. The paper primarily concentrated on middleware implementation for distributed simulation and emphasised the use of real-world data for model verification (Anagnostou & Taylor, 2014).

Fakhimi et al. (2014) conducted research to demonstrate the use of combining ABS and DES models for better strategic planning and simulation analytics. The study used ABS data, which was subsequently entered into the DES model to evaluate different strategies. The study's findings were encouraging, particularly in terms of long-term planning in the healthcare industry. The London Ambulance Service was chosen as a representative healthcare organisation to demonstrate the issues associated with the Triple Bottom Line approach. The authors believe that this hybrid method may be used in a variety of ways to promote sustainable development planning within the context of healthcare.

Day et al. (2014) employed a Hybrid DES-ABS model to study Diabetic Retinopathy among veterans, focusing on the interaction between ABS and DES components. The model used a combination of test and train data for analysis, underlining the need for further development to match real-world dynamics more closely.

Kittipittayakorn and Ying (2016) integrated DES-ABS to enhance patient waiting times in an orthopaedic department. Their study extended beyond simple data analysis to consider patient behaviour, indicating the complexity of accurately modelling a physical examination centre.

Furthermore, Li et al. (2020) and Hamza et al. (2021) explored DES-ABS integration in hospital layout design and patient flow in emergency departments. Their work demonstrated significant improvements in decision-making, efficiency, and patient waiting times.

Moreover, the combination of DES-ABS has the potential to optimise risk assessment by incorporating patients' identities, hospital resource constraints, and queuing dynamics (Elliott et al., 2019). This integration enables a holistic understanding of the intricate interactions within the healthcare system, leading to improved risk management strategies.

Viana et al. (2017) conducted a study aiming to evaluate the effectiveness of home hospital services in Norway using a hybrid approach of DES-ABS. Furthermore, they also used ABS-DES to analyse capacity and patient flow in a post-term pregnancy outpatient clinic (Viana et al., 2018, 2020). The DES component modelled the clinic, while the ABS component represented pregnant women as agents. The models were combined using the interaction mode in AnyLogic. Model validation was primarily based on face validity.

On the other hand, Lassnig et al. (2019) presented a dynamic and adaptive simulation model that integrated ABS with DES, managing heart failure patients in inpatient and outpatient settings. The model incorporated large datasets and introduced four simulation scenarios for two use cases, providing insights into health and economic outcomes. Angelopoulou and Mykoniatis (2022) combined DES and SD to analyse the effects of vaccination on infections. Their study effectively measured individual behaviours and hospital capacities, demonstrating the efficacy of HS.

Anagnostou et al. (2022) developed a hybrid ABS-DES model for managing COVID-19 regionally, combining the FACS and CHARM models. This model enabled predictions about the impact of public health interventions on infection rates and hospital capacity, showcasing the potential for expanding the model to include healthcare staff resources. Developed in Python using SimPy libraries, both models are publicly available. The authors suggest data exchange or middleware for model integration and plan to expand the model to include healthcare staff resources and improve the FACS-CHARM integration.

Zhou et al. (2023) developed a hybrid simulation model using DES and ABS to accurately depict primary care operations. Their model, implemented in AnyLogic, used various double-booking strategies to find an optimal balance between clinic productivity and efficiency.

Penny et al. (2023) introduced a hybrid simulation model for health and social care planning, merging DES with ABS to focus on telecare services for dementia. This model, developed using Simul8, combined DES and ABS and was validated through expert consultation and literature comparison. It assessed the impact of telecare on residential care demand and cost-effectiveness, highlighting the need for more sophisticated models.

Liu et al. (2023) present a hybrid ABS-DES simulation model for optimising resource scheduling in emergency departments, developed with AnyLogic software. The model, featuring state charts and algorithms, allows for customisation to specific ED needs and includes performance evaluations and sensitivity analysis. This approach aims to enhance ED efficiency and patient care, providing a detailed methodology for system building and implementation.

4.3.2.3. Combination of SD and ABS. The combination of ABS-SD has been proven effective in understanding the interaction between population and individual levels when addressing complex problems. Several papers (Djanatliev & German, 2013; Djanatliev et al., 2012, 2014; Kolominsky-Rabas et al., 2015) contribute to the field of prospective health technology assessment (ProHTA), which focuses on evaluating the early effects of new innovations using interdisciplinary knowledge and simulation methods (Djanatliev et al., 2012). In their studies, Djanatliev et al. (2012) developed HS environment for ProHTA. They utilised an SD model to represent population dynamics, disease dynamics, and healthcare financing, while an ABS model was employed to simulate individual workflows. One notable application of this integrated approach was the assessment of the impact of mobile stroke units (MSU), an innovative stroke therapy. This early-stage evaluation of new innovations facilitated decision-making processes (Djanatliev & German, 2013; Djanatliev et al., 2012, 2014). They validated their model by using expert opinion and AnyLogic for model development (Kolominsky-Rabas et al., 2015).

Behavioural analysis is also where hybrid SD-ABS models have been utilised (D. Evenden et al., 2020; D. C. Evenden et al., 2021). The study was carried out on care service planning for individuals with dementia. The researchers developed a model in which the interaction between the model occurred twice – at the onset of dementia and death. The papers demonstrated the significant efficacy of ABS in capturing human behaviours, emphasising its importance in modelling. While ABS has not been extensively employed in recent research, its relevance is increasing. Furthermore, the study highlighted that the integration of ABS and SD provides a comprehensive perspective on the problem by incorporating both stochastic and deterministic elements.

In a different context, Guo et al. (2021) employed a multi-layer hybrid modelling approach to create a COVID-19 model, incorporating both disease transmission and emotional contagion layers. The study suggested that emotional contagion can reduce the number of COVID-19 cases in China, and utilising HS with this emotional layer can yield better outcomes for the model. The model validation was performed using Sensitivity Analysis.

Nguyen et al. (2022) explored the impact of staff working across different care homes on infection rates using an SD-ABS HS model. Their results showed that limiting staff movement and implementing weekly PCR tests effectively reduced infections. The model, developed using AnyLogic, included Network (ABS), Temporary Staff (ABS), and Intra-facility (SD) modules, offering an in-depth analysis of COVID-19 spread dynamics in the UK. Validation involved face validation with domain experts and sensitivity analysis.

Brice et al. (2023) introduced a Hybrid Simulation model combining ABS and SD to model depression progression and treatment, focusing on the UK context. This model evaluates the impact of depression on health services, validated through real-world data comparison, expert opinion, and sensitivity analysis. The model's adaptability for different contexts highlights its efficacy in health service performance evaluation and patient health impact, underlining the ABS-SD integration's effectiveness for complex healthcare challenges.

All the studies above are presented in Table 8 by expressing the methods used, the linking process, validation and verification, and the used software.

4.3.2.4. Combination of DES, SD, and ABS. The study by Viana et al. (2012) was pioneering in combining DES, SD, and ABS, marking a first in our review (see Table 9). In this study, DES simulated the Eye Clinic, SD modelled the dynamics of Age-related Macular Degeneration (AMD), and ABS explored social care scenarios, creating a comprehensive model for AMD patient health and social care analysis. This approach enhanced system understanding and stakeholder engagement, integrating DES and SD into ABS using the Process Environment Mode in AnyLogic software. However, the study didn't explicitly address the validation and verification of the HS approach.

Furthermore, Gao et al. (2014) used SD for population-level analysis and ABS and DES for individual patient simulation in diabetic patient detection. Their study manually integrated these methods using AnyLogic, suggesting potential improvements through the software's automatic integration features.

In a theoretical perspective presented by Djanatliev and Meier (2016), they focused on hospital process modelling using hybrid simulation models. They applied four levels of modelling, combining DES and ABS and enriching them with a surrounding process environment, while an SD model represented population dynamics. This approach provided a comprehensive view of hospital processes, capturing both individual agent behaviours and the broader systemic context.

4.3.3. Validation and Verification

We observed that most of the papers reviewed in this study lack comprehensive explanations of the validation and verification process, particularly in relation to HS. Only 12% of the papers validated both sub-models with statistical and face validity. In addition, 34% of the papers used statistical methods to validate a sub-model, and 15% used face validity to validate one of the sub-models. However, 39% of the papers did not report any validation. While validation methods are applied to validate sub-models, the validation of the entire hybrid model is not clearly explained. It is essential to establish a robust validation process that encompasses the integrated model to ensure its accuracy and reliability.

Table 8. Combination of SD and ABS.

Studies	Method	Linking	Validate/Verify	Software
Djanatliev et al. (2012)	Enriching	Automated	FV-SM	AnyLogic
Djanatliev and German (2013)	Interaction	Automated	FV-SM	AnyLogic
Djanatliev et al. (2014)	Enriching	Automated	NA	AnyLogic
Kolominsky-Rabas et al. (2015)	Enriching	Automated	FV	AnyLogic
D. Evenden et al. (2020)	Interaction	Automated	EV	AnyLogic
Evenden et al. (2021)	Enriching	Automated	EV	AnyLogic
Guo et al. (2021)	Enriching	Automated	SM	AnyLogic
Nguyen et al. (2022)	Interaction	Automated	FV-SM	AnyLogic
Brice et al. (2023)	Sequential	Automated	FV	AnyLogic

Table 9. Combination of DES, SD, and ABS.

Studies	Method	Linking	Validate/Verify	Software
Viana et al. (2012)	Enriching	Automated	NA	AnyLogic
Gao et al. (2014)	Interaction	Manual	SM	AnyLogic
Djanatliev and Meier (2016)	Enriching	Automated	SM	AnyLogic

Upon closely examining the validation process in various studies, it is observed that many rely on data comparison for statistical validation of their models, as exemplified in the works of Li, Zhang, Chi, et al. (2020) and Viana et al. (2020). Other studies have employed methods like regression (Day et al., 2014) or sensitivity analysis (Djanatliev & German, 2013) for model validation. In terms of face validity, various sources such as clinic staff (Viana et al., 2018), department administrators (Ahmad et al., 2014), or domain experts (Kolominsky-Rabas et al., 2015) have been consulted for validating individual models. A notable approach is seen in Nguyen et al. (2022), who utilised multiple validation methods. Their paper details the use of white-box validation, which involves care home stakeholders, alongside black-box validation employing a pattern-oriented modelling approach to replicate patterns observed in UK care homes.

4.4. Study outcome (O)

4.4.1. Level of implementation

In this section, we follow the classification framework established by S. C. Brailsford et al. (2019), categorising the papers into three distinct implementation stages. The first stage is "Proof of Concept", where studies primarily demonstrate the feasibility of HS models in a theoretical or controlled environment. The second stage, "Potential for Real-World Implementation", includes studies that extend beyond theoretical models and suggest practical applications in real-world settings. Finally, the "Actual Real-World Implementation" stage comprises studies where HS models have been effectively implemented and tested in real healthcare settings, showcasing tangible impacts and results.

The analysis of the literature reveals that 73% of the studies use real-world data to validate their models, suggesting potential for real-world implementation of these models (D. Evenden et al., 2020; Liu et al., 2023; Penny et al., 2023; Viana et al., 2017). However, there is no explicit indication that decision-makers have actually employed these models in practice. This implies that while HS is a promising approach, its widespread practical application in healthcare scenarios remains largely theoretical.

Conversely, 18% of the studies are categorised as proof of concept, employing hypothetical scenarios rather than real-world data, and primarily serve illustrative purposes (Ahmad et al., 2013; Hamza et al., 2021; Zulkepli & Eldabi, 2016). A notable exception in our database is the study by Kittipittayakorn and Ying (2016), which details an actual real-world implementation. In their research, the operations of an orthopaedic clinic are analysed, demonstrating that the combination of DES and ABS leads to a reduction in patient waiting times.

4.4.2. Future research direction

Based on the future research needs and gaps identified in the existing literature regarding HS in healthcare, here are proposed future research directions organised into thematic categories. While many studies have paved the way, a few have not explicitly outlined their future research directions.

Our analysis reveals four pivotal areas in future research that emerged consistently across the papers. The first area, "Methodological Improvement", underscores the need for advancements in the methodologies employed in HS, suggesting a continuous evolution and refinement of these techniques. "Data Integration" emerges as the second area, highlighting the importance of integrating diverse data sources to enrich HS models and enhance their accuracy and applicability. The third area, "Application Domain", points to the expanding scope of HS, suggesting its applicability in various healthcare domains beyond those currently explored. Lastly, "Verification and Validation" is identified as a critical area, emphasising the need for rigorous testing and validation of HS models to ensure their reliability and effectiveness in healthcare applications.

The analysis of the papers indicates that methodological improvements are a primary focus (38%) for future research in HS. For example, Zulkepli et al. (2012), Djanatliev et al. (2014), Bell et al. (2016), and Liu et al. (2023). This emphasis is reasonable, given that HS is a developing field where exploring different modelling approaches and combination methods requires further study. Additionally, data integration emerges as the second most popular area (22%) for future research, with researchers expressing interest in applying their proposed models to diverse datasets to assess the broader applicability of these models -i.e., Mielczarek and Zabawa (2016), Lassnig et al. (2019), and Zhou et al. (2023).

Notably, only 2% of the papers prioritise future research on V&V, despite acknowledging that the V&V stages in HS are not fully developed -i.e., Li, Zhang, Chi, et al. (2020). This suggests a potential gap in the current research focus, underscoring the need for more comprehensive attention to the V&V aspects of HS in healthcare.

Based on our understanding from this literature review, future studies should aim to develop more advanced HS models, address the challenges related to validation & verification, enhance model reusability and sustainability, and explore novel approaches for integrating different modelling techniques. The lack of detailed sensitivity analysis in HS in healthcare studies, as identified in our review, opens an avenue for future research. This area presents an opportunity to delve deeper into the robustness and reliability of HS methodologies, thereby contributing significantly to advancements in this field. An additional area for future research lies in the development of standardised guidelines, protocols, and frameworks tailored specifically for the application of HS in Healthcare. These guidelines could outline best practices, recommend methodologies, and provide a framework for addressing specific challenges unique to healthcare systems. By establishing standardised guidelines, the healthcare community can foster a common understanding and language when it comes to HS in healthcare. This would facilitate collaboration, knowledge sharing, and comparability across different studies and settings. Researchers and practitioners would benefit from having a common set of principles and recommendations to guide their work, ultimately leading to improved quality and reliability of HS models in healthcare.

5. Discussion

The review focuses on understanding the various approaches used for combining simulation models, identifying preferred software platforms, and identifying potential research gaps in this field.

In section 4.3.1, the review addresses the first objective by examining the identified frameworks used in healthcare studies. It is revealed that only five distinct frameworks have been identified within the healthcare domain. The findings highlight the prominent frameworks used in healthcare studies, the need for a more accessible model development process, and the importance of considering open-source platforms to enhance model accessibility and foster collaboration. Among these frameworks, the work by Chahal and Eldabi (2008) emerges as the most frequently mentioned Hybrid SD-DES framework in the literature. However, when ABS is taken into consideration, some studies tend to adopt this framework for their research. Another notable framework proposed by J. S. Morgan et al. (2017) is identified in the literature review. This framework introduces sequential, enrichment, interaction, and integration modes as different approaches for combining simulation models. These two frameworks are commonly preferred in healthcare studies involving hybrid simulation. However, it is important to note that these frameworks do not provide a methodological step-by-step computer simulation development process that is easily accessible for individuals new to hybrid simulation.

While various model combination approaches exist, our findings show that the choice of framework ultimately depends on the preferences of the modellers. However, it becomes apparent that there is a need for an additional framework that not only explains the selection process for the preferred model combination format but also provides a more user-friendly and accessible approach, particularly new to hybrid simulation researchers and practitioners.

The papers reviewed often lack comprehensive explanations of their model development stages, particularly regarding the methods used for model parameterisation. While a significant portion (33%) of the papers reference data-driven methods for setting model parameters, others employ different approaches such as the design of experiments (2%), expert opinion (7%), and a combination of data-driven methods and expert opinion (2%). However, many papers do not specify the methods used for model parameterisation.

Furthermore, a significant majority of the reviewed papers (58%) indicate a preference for using the AnyLogic software for developing hybrid models. AnyLogic provides modellers with the capability to seamlessly integrate different simulation approaches within the software. All the modellers used the combination of SD-ABS preferred AnyLogic for the model. However, it is important to acknowledge that the reusability of models created in AnyLogic might pose challenges due to the limited public accessibility of the software.

On the other hand, only a small percentage (8%) of the studies opted for open-source platforms to develop their models. However, it can be argued that the adoption of open-source platforms in HS studies has the potential to drive meaningful advancements and create a more interconnected and dynamic landscape. Open-source platforms can also provide a transparent and inclusive environment that empowers researchers to openly share their models, methodologies, and findings. Therefore, researchers may be encouraged to consider transitioning their HS studies to open-source platforms. By embracing open-source approaches, researchers can facilitate knowledge exchange, encourage reproducibility, and invite contributions from a wider pool of experts. This collaborative spirit not only promotes innovation but also strengthens the rigour and reliability of HS research in diverse fields, including healthcare.

Validation of the model is typically conducted by comparing the results with previously developed models or real-world data. Additionally, face validity is achieved by gathering opinions from clinic staff or administrators through focus groups or meetings. External validity, which refers to the generalisability of the model to real-world healthcare contexts, is an important aspect to consider in HS. The reviewed papers would benefit from providing more insights into the external validity of their models and how they can be applied in different healthcare settings. Mustafee et al. (2015) at the effectiveness of a combined method is greater than that of its individual components. This indicates that integrating different methods may yield outcomes different from those produced by each method separately. The interactions between various components can generate new behaviours or dynamics, which might not be evident when each model is verified in isolation. Consequently, it is crucial to ensure that these interactions are accurately represented and function as intended. While there are some notable methodological works on the validation and verification of single simulation methods (Barlas, 1996; Ormerod & Rosewell, 2006; Raunak & Olsen, 2015), our review shows that many HS in healthcare studies do not detail their validation and verification process. This recognition of the complexities involved in verifying hybrid models in healthcare not only highlights current gaps but also paves the way for future research. Such research could focus on developing specialised methodologies and best practices for the verification of HS, ensuring more robust and reliable models in healthcare applications.

Moreover, many of the models developed in the literature are tailored to specific research scenarios. While some studies provide explanations for using HS and its methodology, the majority focus on problem-specific modelling, limiting the generalisability of their models to other healthcare problems. It is crucial to develop a framework that demonstrates how different modelling approaches can be connected in a flexible manner, allowing for broader applicability across various healthcare contexts. Such a framework would facilitate future research endeavours by providing guidance on the integration of different modelling methods and promoting the development of more versatile and transferable HS models.

This literature review provides compelling evidence that HS is a more effective approach for comprehending complex systems, particularly in healthcare. The limitations of single models have prompted researchers and modellers to explore alternative methods to address the intricate challenges posed by complex healthcare systems. Decision-makers need to consider not only department-specific factors but also the interdependencies and interactions within the entire system. HS offers a promising solution by integrating different modelling techniques and providing a holistic perspective that enables the optimisation of performance within the overall healthcare system.

Moreover, in a rapidly changing world, it is imperative to develop sustainable and reusable models that can effectively identify and address problems within the healthcare system. HS, with its ability to incorporate multiple modelling approaches, provides a flexible and adaptable methodology that can capture the dynamics and complexities of the healthcare environment. This adaptability is crucial as the healthcare system often faces global challenges, such as pandemics or shifts in healthcare policies, requiring swift decision-making and the ability to model and evaluate various scenarios. HS allows for the rapid integration of new data and parameters, facilitating timely decision-making and enabling healthcare organisations to respond effectively to emerging challenges.

The significance of HS is further underscored by the need for comprehensive, system-wide optimisation in healthcare. The interconnectedness of various components and the influence of different factors on the overall system necessitate an approach that can capture these complexities and provide insights into system-wide improvements. HS enables the exploration of various interventions, policies, and strategies, considering their effects on the entire healthcare system rather than focusing solely on individual components.

6. Conclusion

This literature review highlights the effectiveness of HS in comprehending complex healthcare systems. The limitations of single models, the need for system-wide optimisation, the demand for adaptable and sustainable modelling approaches, and the rapid changes in the healthcare landscape emphasise the increased significance of HS. By leveraging the strengths of different modelling techniques within a hybrid framework, HS provides a powerful tool for decision-making and problem-solving in healthcare. Further research in this field is essential to harness the full potential of HS and advance the understanding and application of simulation modelling in healthcare.

Leveraging the capabilities of software packages can enhance the efficiency and effectiveness of model integration, enabling researchers to explore complex healthcare scenarios more comprehensively. However, utilising open-source platforms may also enhance the accessibility of models and fostering broader collaboration within modellers. Given the potential and advantages offered by HS, there is a clear need for continued research in this domain.

Our review identifies several critical factors essential for the effective implementation of HS in healthcare. First, transparency in addressing and rationalising uncertainties is important for enhancing the credibility and reliability of the models. Notably, our findings reveal that most studies do not provide detailed strategies for handling uncertainty in HS within the healthcare context, indicating an area for future research. Secondly, the clear definition and demarcation of sub-models, along with their boundaries, are essential for comprehending the system as a whole. This includes providing detailed documentation on how parameters for each sub-model are derived, which is crucial during the model development stage. Thirdly, articulating the interaction between models and the key parameters linking the sub-models is vital. Such clarity is fundamental for users to understand the nuances of hybrid operations and for ensuring the model's applicability to real-world scenarios. Finally, model validation and verification require thorough explanations to establish the model's accuracy and appropriateness for healthcare applications. These factors collectively contribute to the robustness and efficacy of HS in healthcare, paving the way for more nuanced and effective healthcare models in future research and practice.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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