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Systematic Review

Systematic Review of Discrete Event Simulation in Healthcare and Statistics Distributions

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Abstract: The healthcare sector, as a complex industrial system, faces significant challenges in delivering quality care amid resource constraints, driving the increased adoption of discrete event simulation (DES) as a tool for enhancing operational efficiency. While DES has proven valuable in healthcare operations, there is limited understanding of the statistical distributions employed in its implementation and its technological evolution. This study conducts an innovative review examining the diffusion of DES in health services, analyzing both the statistical distributions used in medical services simulation and the advancement of DES technologies. Through a comprehensive analysis of 616 publications from 2010 to 2022, we investigated DES utilization patterns and technological evolution and conducted a comparative analysis between pre- and post-COVID-19 pandemic periods, evaluating publication trends by country. The results reveal a significant increase in DES publications, an expansion of journals publishing DES-related articles, and notable technological advancements in simulation capabilities, particularly following the COVID-19 pandemic. These findings demonstrate the growing relevance of DES in healthcare research and its crucial role in process automation and decision-making within the industrial healthcare environment.

Keywords: literature review; simulation; healthcare; hospitals; patients; DES

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Academic Editor: Alexandre Carvalho

Received: 26 December 2024
Revised: 4 February 2025
Accepted: 6 February 2025
Published: 11 February 2025

Citation: Vecillas Martin, D.; Berruezo Fernández, C.; Gento Municio, A.M. Systematic Review of Discrete Event Simulation in Healthcare and Statistics Distributions. *Appl. Sci.* **2025**, *15*, 1861. https://doi.org/10.3390/app15041861

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1. Introduction

The healthcare sector has evolved into a sophisticated industrial system, with hospitals operating as complex production environments where patient care processes must be optimized similar to manufacturing operations [1]. This sector has experienced significant expenditure increases over recent decades [2], driving a continuous search for process improvement to reduce costs and meet growing patient demand [3]. In this context, discrete event simulation (DES), first developed in the late 1950s [4], has emerged as a crucial tool for analyzing and optimizing complex systems [5].

The industrial approach to healthcare management has become increasingly relevant as healthcare organizations face challenges similar to those in manufacturing: resource allocation, process improvement, quality control, and efficiency improvement [6]. While DES has proven valuable across various industrial sectors [7], including transport [8] and manufacturing [9], its application in healthcare has become particularly significant for modeling patient flows and resource utilization without directly impacting patient care.

Healthcare organizations increasingly rely on DES to better understand and improve process behavior, including patient flows [10,11], workflows [12,13], and computer systems [14]. The simulation's ability to model scenarios without affecting actual patients

makes it especially valuable for healthcare management. Multiple software tools support these applications, including ARENA, Simul8, AnyLogic, ProModel, and FlexSim, enabling researchers and practitioners to model complex healthcare systems effectively.

The technological evolution of DES has paralleled the advancement of Industry 4.0, incorporating emerging technologies such as artificial intelligence, Internet of Things (IoT), and cloud computing [15]. These technological integrations have enhanced DES capabilities in healthcare settings, enabling more accurate modeling, real-time decision support, and improved stakeholder engagement [16].

Despite the extensive literature on DES applications in healthcare, a significant gap exists in understanding the statistical distributions employed in these simulations. While previous reviews have examined various aspects of DES implementation, none have comprehensively analyzed the statistical distributions used in healthcare case studies. This analysis is crucial as these distributions fundamentally affect the accuracy of real-life situation modeling and subsequent decision-making quality.

This study presents a systematic review of DES applications in healthcare between 2010 and 2022, examining publication patterns by country, implementation across medical services, software usage, and achieved improvements. Importantly, we provide the first comprehensive analysis of statistical distributions utilized in healthcare DES implementations. The paper is structured as follows: Section 2 presents the methodology following PRISMA guidelines; Section 3 provides a comprehensive analysis of publication trends and patterns; Section 4 presents an in-depth discussion covering software analysis, application areas, implementation improvements, statistical distributions, technological evolution, and implementation implications; and Section 5 presents our conclusions and recommendations for future research.

2. Materials and Methods

Our systematic review methodology followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [17,18], ensuring a comprehensive and reproducible research process.

2.1. Information Sources and Search Strategy

We conducted a systematic search across three major healthcare-focused databases: PubMed, Scopus, and Web of Science (WOS). The search was performed in December 2022, focusing on English-language articles published between January 2010 and December 2022. To ensure research quality, we included only peer-reviewed journal articles while excluding conference proceedings, book series, and articles without abstracts. The search strategy utilized key terms “discrete-event simulation”, “health-care”, and “hospital” in the title and/or abstract fields (“tiab”).

The specific search strings employed for each database are detailed in Table 1, which resulted in initial identification of 2547 publications across all databases (PubMed: 291; Scopus: 1237; WOS: 1019).

Table 1. Search strings used in the literature review.

Database	Search	Publications
PubMed	“discrete-event simulation”[tiab] AND (“health care”[tiab] OR “hospital*”[tiab])	291
Scopus	TITLE-ABS-KEY ((“discrete-event simulation”) AND (hospital* OR (“health care”))) AND PUBYEAR > 2009 AND PUBYEAR < 2023 AND (LIMIT-TO(LANGUAGE, ”English”))	1237
WOS	(discrete-event simulation) AND (hospital* OR “health care”)	1019

2.2. Study Selection Process

The included studies focused on discrete-event simulation applications in healthcare settings, specifically in hospitals. Studies were required to be written in English, published in peer-reviewed journals between January 2010 and December 2022, and contain a digital object identifier (DOI). The studies needed to demonstrate practical applications of DES in healthcare environments, including patient flow analysis, resource management, or process improvement initiatives. Conference proceedings, book series, articles without abstracts, and retracted publications were excluded from the analysis.

The final analysis included 616 publications, of which 349 were case studies that formed the core dataset for our detailed analysis. All data associated with this systematic review, including the complete list of analyzed publications and their characteristics, will be made available through the Supplementary Materials Annex S1.

2.3. Data Collection

The systematic search process identified 2547 publications across the three databases, as illustrated in Figure 1. Following the removal of 842 duplicates through EndNote X9 (using both automatic de-duplication and manual checking), 1705 articles remained for initial screening. During the screening process, 751 articles were excluded due to missing DOI or retraction status, and 269 publications were not accessible for full-text review. Of the remaining 954 articles that underwent full-text examination, 69 were eliminated for not meeting the inclusion criteria.

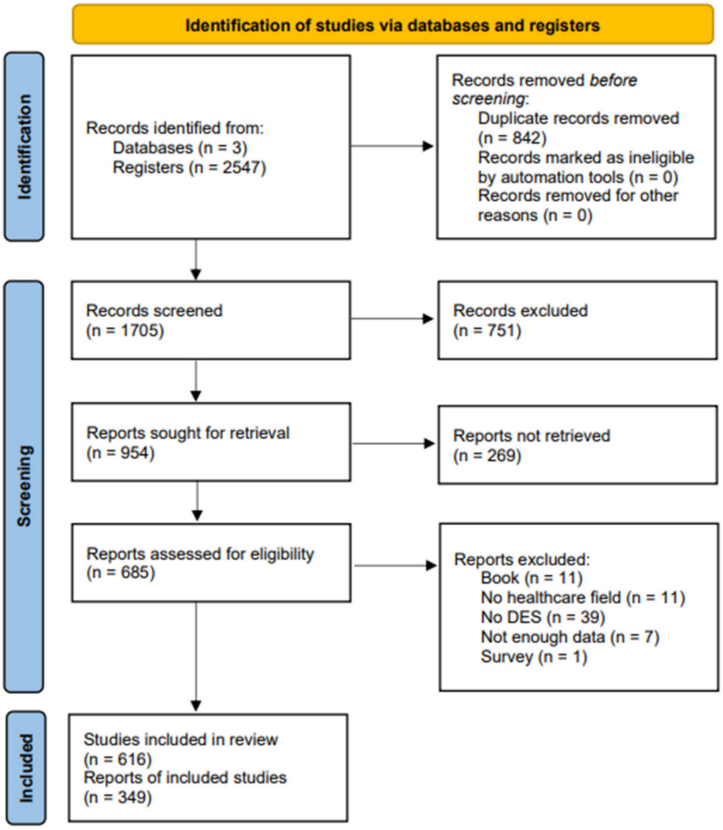

Figure 1. PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only.

The final analysis included 616 publications, comprising case studies, action research, reviews, and theoretical–conceptual papers. From these, 349 publications were identified as case studies and were selected for detailed analysis. The present article focuses exclusively

on these case studies, examining their methodological approaches, implementation contexts, and reported outcomes in healthcare settings.

3. Results

We conducted a bibliometric analysis on all retrieved publications. Specifically, our statistical analysis includes publication trends over time, country of the publications, application areas in the hospitals simulated, improvements achieved in the medical service and DES software used.

3.1. Publication Trends over Time

The literature on discrete event simulation (DES) in health services has experienced a remarkable growth in recent years. As illustrated in Figure 2, the number of publications in this area was merely 26 in 2010, but by 2022, the cumulative count had reached 616 papers across various journal types (excluding books and surveys). This exponential growth of DES publications in health research can be attributed to the expanding pool of adopters and dissemination channels for this research approach [19]. Among these publications, the majority (349 papers) take the form of case studies, highlighting the practical application of DES in analyzing healthcare systems.

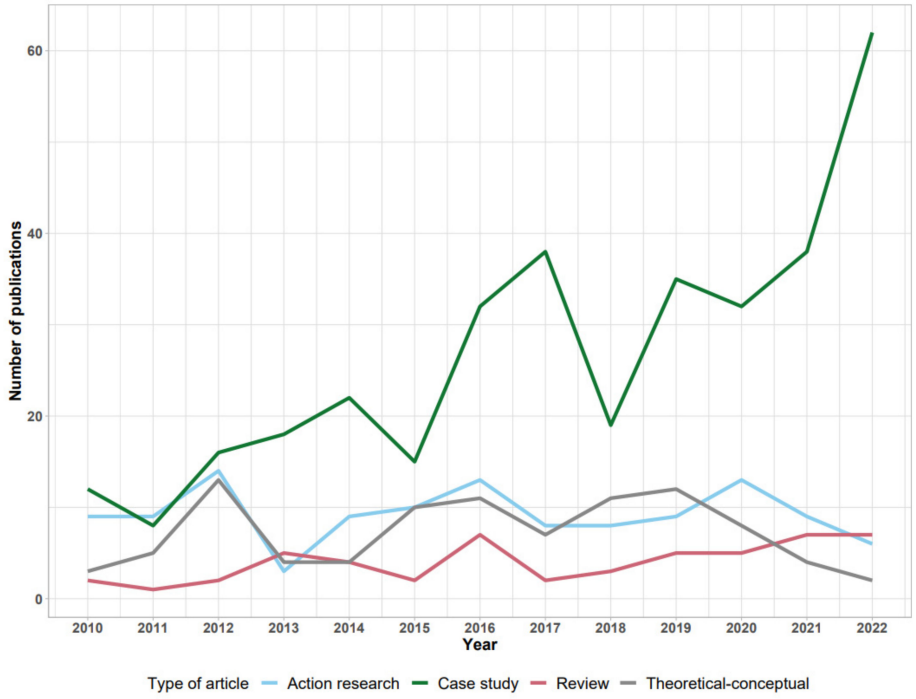

Figure 2. Annual publications by type of article.

3.2. Country of the Publications

The articles included in the analysis, grouped by the country in which they were developed, are shown in Table 2. In terms of the country focused on in the research articles, most of the publications come from the USA (26.4% of the articles), UK (17.4%), and Canada (6%), while Italy, Netherlands, Australia, Germany, France, and Spain account for 20.7% of the total of published papers. The sum of the values of the table is greater than the analyzed articles because there are publications with more than one country.

We have data on the number of publications from 2010 to 2022, which makes it relevant to differentiate between two distinct periods: before the COVID-19 pandemic (2010–2019) and after the pandemic (2020–2022). The sum of the number of countries exceeds the number of publications because some journals analyze multiple countries. This implies

that within certain journals, there are publications that encompass research and analysis conducted in more than one country, resulting in a higher count of countries compared to the total number of publications. This indicates a broad international perspective and the consideration of multiple geographical contexts within the scope of the analyzed journals.

Table 2. Number of publications by country.

Country	Number of Publications (%)
USA	170 (26.4)
United Kingdom	112 (17.4)
Canada	39 (6)
Italy	29 (4.5)
Netherlands	25 (3.9)
Australia	23 (3.6)
Germany	20 (3.1)
France	18 (2.8)
Spain	18 (2.8)
Others	191 (29.5)

During the period before the pandemic, there was a steady increase in the frequency of publications on discrete event simulation in the healthcare sector. Several countries, especially those with more developed healthcare systems such as the United States, the United Kingdom, and Canada, had a higher number of publications. These countries have greater financial resources and research capabilities, which allows them to lead in scientific production in this field.

The COVID-19 pandemic had a significant impact on scientific production related to discrete event simulation in the healthcare sector. In the years following the onset of the pandemic, there was a drastic increase in the number of publications in this field. Researchers focused on better understanding the spread of the virus, evaluating intervention strategies, and improving healthcare planning. There was greater participation from countries around the world in generating research on discrete event simulation in the healthcare sector.

The comparison between the periods before and after the pandemic revealed significant differences in the evolution of publications. While a constant growth was observed before the pandemic, an exponential increase in scientific production occurred after the pandemic. The global health crisis generated by the pandemic spurred research and the development of new strategies based on discrete event simulation.

The table with the number of publications by country and year is shown in the Supplementary Materials Annex S1 of this article.

3.3. Journals

Among the 616 scrutinized publications, we examined 292 unique journals spanning the years 2010 to 2022. This reveals a wide variety of academic and scientific sources, underscoring the comprehensive nature of our analysis (Table 3).

One notable aspect is the extensive dispersion of publications across journals. Only 7 journals have reached a maximum of four publications in a single year, while 13 journals have achieved three publications, and 33 journals have published two articles. This distribution highlights the diverse range of sources and indicates a relatively even distribution of publications among the journals analyzed.

The distribution of publications across journals reveals interesting patterns in how DES research is disseminated within the healthcare community. While PharmacoEconomics leads with 21 publications (3.41%), the broad distribution across 292 journals suggests that DES applications in healthcare have relevance across multiple disciplines. The presence of both operations research journals (Journal of the Operational Research Society, Operations

Research for Health Care) and healthcare management journals (Health Care Management Science, Medical Decision Making) indicates the interdisciplinary nature of DES applications. This diverse distribution also suggests that DES research reaches different audiences, from healthcare practitioners to operations researchers, potentially facilitating knowledge transfer across disciplines.

Table 3. Number of publications by journal.

Journal	Number of Publications (%)
PharmacoEconomics	21 (3.41)
Value in Health	18 (2.92)
Journal of the Operational Research Society	17 (2.76)
Health Care Management Science	16 (2.60)
Medical Decision Making	14 (2.27)
Operations Research for Health Care	14 (2.27)
European Journal of Operational Research	13 (2.11)
IISE Transactions on Healthcare Systems Engineering	10 (1.62)
PLOS ONE	10 (1.62)
Simulation Modelling Practice and Theory	10 (1.62)
Others	473 (76.80)

However, it is important to highlight that 204 journals have only one publication each, indicating a dispersion of articles across a large number of sources.

The table with the number of publications by journal and year is shown in Supplementary Materials Annex S1 of this article.

4. Discussion

The exponential growth of scientific publications in healthcare simulation reflects a broader trend in medical research where data-driven decision-making has become increasingly crucial. Similar to other rapidly evolving fields in healthcare, such as artificial intelligence and machine learning, the challenge lies not only in producing research but in effectively synthesizing and applying existing knowledge. This challenge is compounded by varying publication quality, accessibility issues, language barriers, and the constant need for current information. Our systematic review addresses these challenges by providing a comprehensive analysis of DES applications in healthcare, building upon previous reviews but offering novel insights into the statistical foundations of simulation models.

Our analysis reveals that while DES software tools have evolved significantly since their introduction in the 1950s, their fundamental purpose remains constant across platforms. Arena's emergence as the most widely used software aligns with findings from previous industrial and healthcare simulation studies, suggesting a consolidation of preferred tools in the field. This trend parallels the evolution of other analytical tools in healthcare, where standardization has facilitated broader adoption and reliability.

A significant finding of our review, distinguishing it from previous systematic reviews (see Figure 1 and Supplementary Materials Annex S1), is the critical role of statistical distributions in DES implementation. While prior reviews have focused on operational outcomes or specific healthcare applications, none have systematically examined the statistical underpinnings of these simulations. This gap is particularly noteworthy given that statistical distributions fundamentally influence model accuracy and, consequently, decision-making reliability.

The absence of a universal DES model in healthcare applications, as revealed by our analysis, emphasizes the importance of context-specific modeling approaches. This finding aligns with previous healthcare modeling studies that highlight the uniqueness of each healthcare environment. Our review extends this understanding by demonstrating how sta-

tistical distribution selection must be tailored to specific healthcare contexts, often requiring direct input from healthcare workers through field interviews to ensure model accuracy.

The diversity of DES software applications identified in our review (Arena, Simul8, AnyLogic, and ProModel) reflects the field's maturity and the varying needs of healthcare institutions. While these platforms share common objectives in modeling complex systems, their continued co-existence suggests that different healthcare contexts may benefit from different simulation approaches, a finding that has significant implications for future implementation strategies.

4.1. Software

Figure 3 shows the discrete event simulation software that has been applied in the case studies identified in the articles. Our analysis reveals Arena as the dominant software choice, followed by Simul8, a finding that aligns with previous studies on simulation software adoption in healthcare settings. Arena's prevalence, particularly in the USA healthcare sector, can be attributed to multiple factors identified in prior research: its established industry reputation, extensive support community, and large user base in the healthcare industry, which facilitates collaboration and resource sharing among healthcare professionals [20].

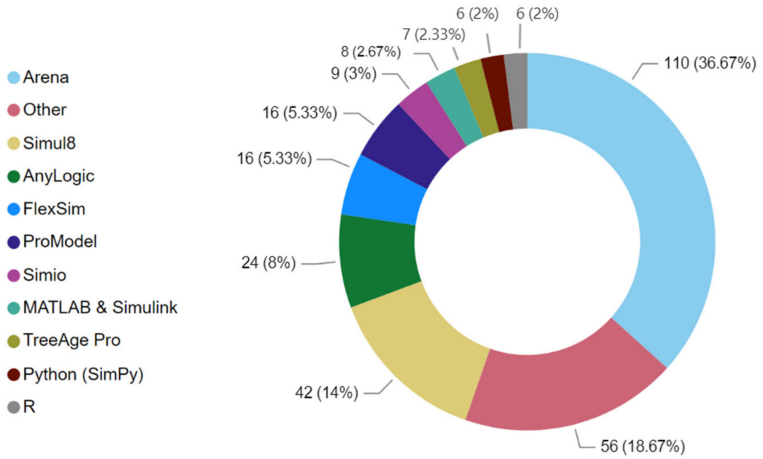

Figure 3. DES software implemented in the case studies.

Interestingly, our analysis identified several comparative studies where multiple software platforms were used within the same case study [21–27]. This trend of software comparison reflects a growing sophistication in the healthcare simulation community, where practitioners are increasingly focused on identifying the most appropriate tools for specific contexts. The fact that the sum of software implementations exceeds the 349 analyzed case studies due to these comparative studies suggests a methodological maturity in the field, where researchers are actively evaluating and comparing different simulation approaches.

These findings provide insights into DES software usage patterns in healthcare settings. While Arena's prevalence is notable, particularly in academic research, the successful implementation of multiple software platforms suggests that effective healthcare simulation can be achieved with various tools. Software selection, in practice, is influenced by multiple factors including institutional capabilities, existing infrastructure, user expertise, cost considerations, and integration requirements with hospital information systems. This multi-factorial approach to software selection aligns with Katsaliaki and Mustafee's [5] findings on the practical considerations in healthcare simulation implementation. Our analysis highlights distinct advantages and limitations among major DES platforms, particularly in their applicability to different healthcare contexts.

4.1.1. Software Capabilities and Features

Comprehensive evaluations by Tako and Robinson [28], expanded by recent studies, have identified key differentiating features among leading DES platforms. Arena, widely used in healthcare modeling, offers an extensive library of healthcare-specific modules and strong process-oriented modeling capabilities. However, it has limited built-in optimization tools and presents a moderate learning curve for healthcare professionals. In contrast, Simul8 is recognized for its intuitive user interface, facilitating rapid model development, and its built-in healthcare reference models. Despite its strong visual animation capabilities, it struggles with handling complexity in large-scale models. AnyLogic stands out for its hybrid simulation capabilities, integrating discrete event simulation (DES), agent-based modeling (ABM), and system dynamics (SD). It also provides advanced analytics and sophisticated visualization options, though at the cost of a steeper learning curve.

Research by Swisher et al. [29] demonstrated that software selection significantly influences model development time and implementation success. Their comparative analysis found that Arena reduced development time by 25% compared to general-purpose simulation tools in complex healthcare models, emphasizing the impact of tailored software solutions.

4.1.2. Context-Specific Performance

The suitability of a DES platform varies depending on the healthcare environment. Studies by Günal and Pidd [30] found that in emergency department (ED) modeling, Arena and Simul8 performed particularly well due to their robust queue-handling capabilities, while AnyLogic's agent-based features provided a more detailed representation of patient behavior variations. Despite these differences, all three platforms demonstrated comparable accuracy in throughput prediction.

For outpatient clinics, Simul8 proved especially effective, with its healthcare templates reducing model development time by 40%. Arena's process analyzer facilitated superior scenario analysis, while AnyLogic offered better integration with scheduling systems, making it a strong choice for environments requiring dynamic appointment management.

4.1.3. Integration and Modern Requirements

The growing need for interoperability between simulation software and hospital information systems has made integration capabilities a key factor in software selection. Katsaliaki and Mustafee [5] identified notable differences in this regard. Arena supports structured API access, facilitating system interoperability, while Simul8 offers direct database connectivity, enabling seamless data exchange. AnyLogic provides the most comprehensive support, integrating both API-based and database-driven interactions.

4.1.4. Implementation Considerations

Beyond technical capabilities, practical factors also influence software selection. Research by Jacobson et al. [31] highlights key considerations, including cost-related aspects such as initial licensing fees, training requirements, maintenance, and integration expenses. Additionally, technical requirements such as hardware specifications, network connectivity, database compatibility, and security features play a crucial role in determining the feasibility of implementation within healthcare institutions.

4.1.5. Future Trends

Recent developments analyzed by Monks et al. [32] indicate a shift toward more integrated and accessible simulation platforms. The adoption of cloud-based collaboration tools, enhanced mobile accessibility, and improved interoperability with hospital systems

is becoming increasingly important. Furthermore, advancements in visualization technologies are expected to facilitate more intuitive and interactive simulation environments, enabling stakeholders to derive greater insights from complex healthcare models.

4.2. Application Areas

In terms of application areas, our analysis revealed that a significant portion of the case studies, i.e., 90 (25.8%) publications, focused on the Emergency Department (ED). This was followed by generic models, with 35 (10%) publications, and the Oncology Department, with 31 (8.9%) articles. This distribution pattern builds upon previous research that has identified these areas as particularly challenging for healthcare management and improvement.

The prominence of DES articles in the ED and oncology areas can be attributed to the high complexity and variability of these healthcare systems. Both areas face challenges such as high patient volumes, limited resources, and unpredictable patient arrivals, especially in the Emergency Department, making it difficult to optimize patient flow and resource utilization. DES serves as a valuable tool for modeling and analyzing these intricate systems, enabling researchers to identify bottlenecks, analyze processes, and ultimately enhance patient outcomes.

The majority of articles concentrate on the ED, which is a critical area due to its association with prolonged wait times, increased morbidity and mortality rates, and reduced patient satisfaction. Reducing wait times in the Emergency Department is a challenging task [33]. The ED is a highly dynamic service that requires frequent reviews and updates to minimize patient waiting times (WT), which directly impact other patients and can prevent the need for patient transfers to other hospitals during periods of saturation.

Previous studies have demonstrated that DES has proven effective in improving the ED by reducing WT and increasing service capacity [34–36]. However, our analysis reveals that some healthcare departments, such as gynecology, urology, and obstetrics, among others, have a smaller number of publications.

Figure 4 shows all the application areas identified in the reviewed articles.

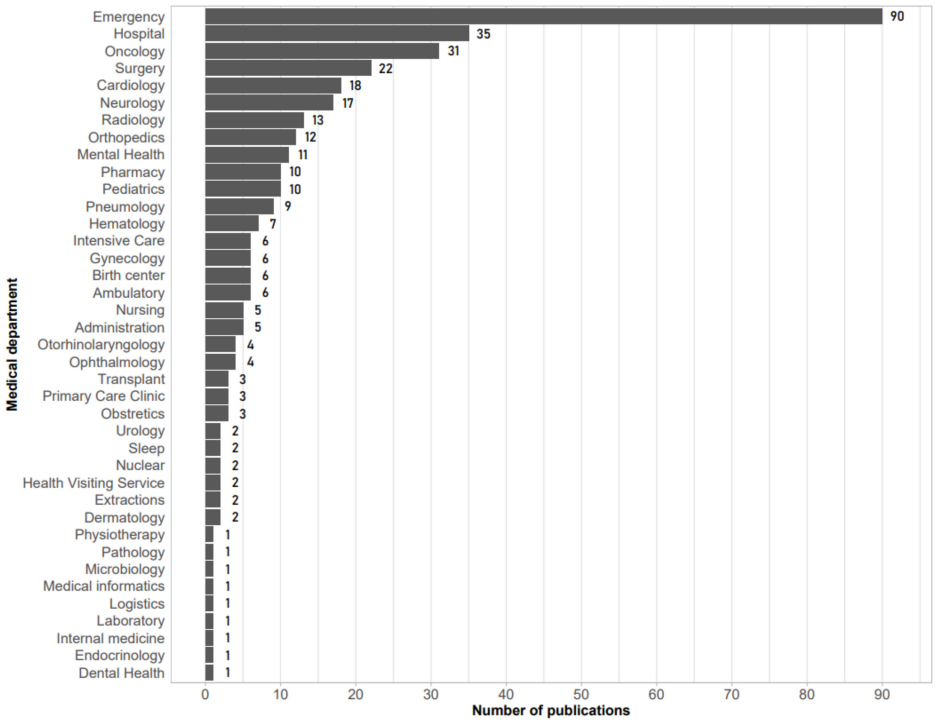

Figure 4. Medical departments and number of publications.

Our analysis highlights its successful application across various medical departments, each presenting unique challenges and opportunities for process improvement.

4.2.1. Emergency Department Applications

Emergency Departments account for 25.8% of analyzed DES applications, reflecting their complex patient flows and critical need for resource optimization. Saghafian et al. [37] demonstrated that DES models in EDs primarily focus on improving patient flow, optimizing resource allocation, refining triage processes, and enhancing capacity planning. Their study reported an average 25% reduction in waiting times through DES-guided process improvements, underscoring the impact of simulation-driven interventions in high-demand environments.

4.2.2. Surgical Services and Operating Rooms

Operating rooms pose distinct logistical challenges that DES has proven effective in addressing. Vanberkel et al. [38] documented implementations aimed at optimizing surgical scheduling, managing recovery room capacity, improving staff allocation, and enhancing equipment utilization. Their analysis of a major surgical department revealed that DES-based scheduling strategies increased operating room utilization by 18% while reducing overtime by 32%, demonstrating the potential for simulation to enhance both efficiency and cost-effectiveness in surgical services.

4.2.3. Outpatient Clinics

The application of DES in outpatient clinics has grown considerably, as highlighted by Mohiuddin et al. [39]. Simulation models in these settings focus on optimizing appointment scheduling, managing patient flow, and improving resource allocation to better align capacity with demand. A systematic review of 22 outpatient clinic implementations showed that DES-optimized scheduling reduced patient waiting times by 15–30%, illustrating its effectiveness in improving operational efficiency and patient experience.

4.2.4. Oncology Services

Cancer treatment facilities face intricate scheduling demands due to the complexity of chemotherapy and radiation therapy regimens. Liang et al. [40] documented DES applications that enhance chemotherapy scheduling, optimize treatment room usage, and improve staff allocation. Their study in a major cancer center demonstrated a 24% increase in chemotherapy chair utilization while reducing patient waiting times by 17%, highlighting the value of DES in balancing high-demand care with limited resources.

4.2.5. Laboratory and Diagnostic Services

Laboratory operations benefit significantly from DES-driven workflow optimization. Hayes et al. [41] identified applications in streamlining test processing, enhancing equipment utilization, improving staff scheduling, and optimizing result reporting. Their findings showed a 22% increase in throughput following process redesign guided by DES, demonstrating its capacity to enhance diagnostic efficiency and turnaround times.

4.2.6. Intensive Care Units

The critical nature of Intensive Care Units (ICUs) necessitates precise capacity planning and resource management. Griffiths et al. [42] documented DES applications in optimizing bed occupancy, allocating staff efficiently, and improving patient flow. Their study showed that DES-based capacity planning reduced ICU admission delays by 28%, emphasizing the role of simulation in mitigating bottlenecks in high-acuity care settings.

4.2.7. Cross-Departmental Integration

A growing area of DES research focuses on modeling interactions between departments to enhance system-wide efficiency. Harper et al. [43] demonstrated that integrated DES models encompassing multiple departments achieved 15% greater overall efficiency, improved resource allocation, and provided more realistic predictions of hospital-wide impacts. Their findings underscore the importance of cross-departmental simulation in capturing interdependencies and enhancing the effectiveness of healthcare operations.

4.3. Improvements

Our analysis of DES implementations in healthcare settings reveals significant patterns in achieved improvements, building upon previous research that identifies efficiency enhancement, quality improvement, and cost reduction as fundamental healthcare objectives [44]. The findings demonstrate how simulation projects offer multiple benefits, including reduced experimentation costs, shorter project times, and enhanced outcomes [24].

A key methodological aspect of these improvements lies in the simulation's scalability to create events and times for medical departments across various scenario lengths. The robustness of results is ensured through multiple model replications using real patient data in each iteration, a practice that aligns with established simulation methodologies in healthcare research.

As illustrated in Figure 5, our analysis revealed several significant improvements across the analyzed case studies:

- Waiting time (WT) reduction in 111 publications (31.8%).
- Service cost reduction in 84 studies (24%).
- Service capacity increase in 63 cases (18%).

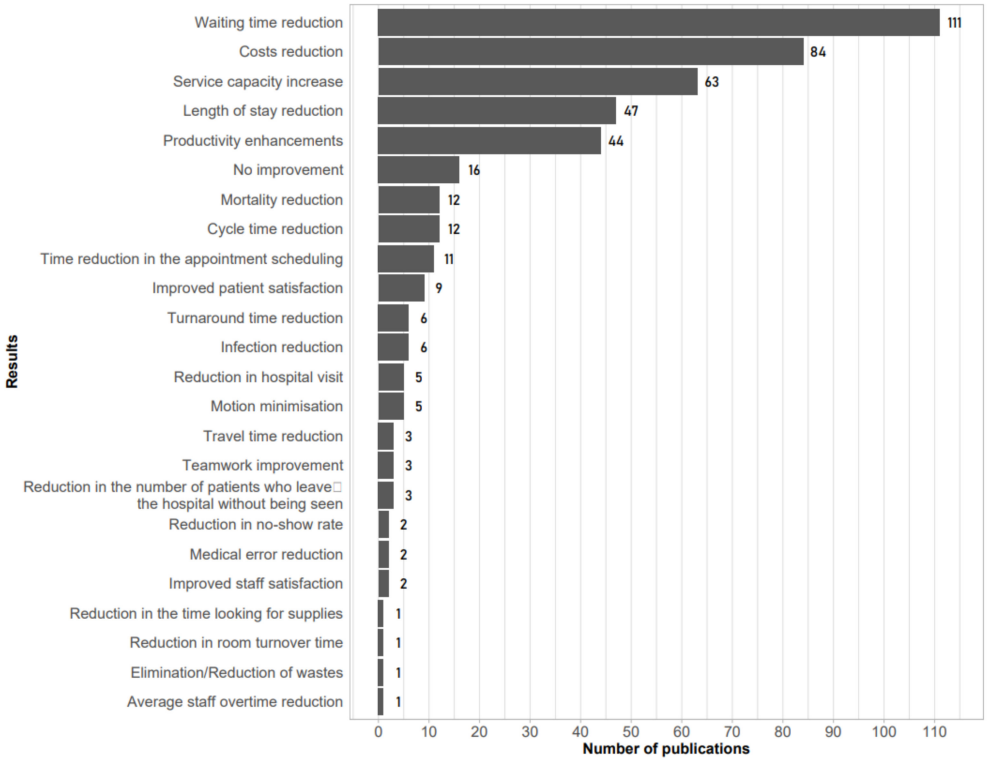

Figure 5. Results of the simulation.

Notably, only 16 publications (4.6%) reported no quantitative improvements, while the majority achieved at least one measurable enhancement. A particularly significant finding is that 83 case studies (23.7% of the total) achieved multiple improvements simultaneously,

suggesting the potential for DES to address multiple healthcare challenges concurrently. This aligns with previous research [45] demonstrating that DES enables process improvement without directly impacting patient care during the simulation process.

The fact that the sum of improvements in Figure 5 exceeds the 349 case studies analyzed indicates a trend toward comprehensive optimization, where single DES implementations often yield multiple benefits. This finding has important implications for healthcare institutions considering DES implementation, suggesting the following:

- DES can simultaneously address multiple operational challenges.
- Investment in DES might yield broader benefits than initially targeted.
- Healthcare institutions should consider multiple improvement metrics when evaluating DES success.

These results point to several promising directions for future research:

- Investigation of factors contributing to multiple simultaneous improvements.
- Development of frameworks for maximizing multiple benefits from single DES implementations.
- Exploration of potential synergies between different types of improvements.
- Analysis of long-term sustainability of achieved improvements.

4.4. Analysis of Statistical Distributions

The selection of appropriate statistical distributions in healthcare DES models significantly impacts simulation accuracy and reliability. Our comprehensive analysis reveals patterns in distribution selection across different healthcare processes, while acknowledging the context-specific nature of these choices. Through detailed examination of the 349 case studies, we identified distinct patterns in distribution usage across various healthcare processes.

The inclusion of travel time in simulations [46,47] becomes particularly relevant when modeling patient transfers to different facilities or hospitals or when transferring to other departments within the same hospital. Notably, we observed that registration times were not consistently addressed in the literature.

Furthermore, our analysis showed that the distributions we identified may work well for some medical departments, but they may not be as suitable for others. This indicates that there is no one-size-fits-all statistical distribution that can be universally applied. Our aim was to investigate the distributions that are commonly used and recognized in the field of discrete event simulation (DES).

Table 4 presents the statistical distributions that were identified in the reviewed literature.

Table 4. Statistical distributions and discrete events.

Event	Discrete Event	Statistical Distribution (Number of Appearances)
Patient Flow	Arrival	Poisson (25); Normal (5); Johnson (2)
Patient Flow	Interarrival time	Exponential (11)
Patient Flow	Length of stay (LOS)	Lognormal (6); Erlang (1); Normal (4); Weibull (3); beta (1); Pearson (2); Gamma (2); Exponential (2)
Operational	Process time	Lognormal (1); Triangular (4); Normal (1); Weibull (2);
Operational	Activity durations	Uniform (1); Triangular (3)
Operational	Service times	Beta (1); Uniform (1); Triangular (5); Exponential (4)
Support	Administrative tasks	Johnson (1)
Support	Travel times	Lognormal (1); Triangular (4); Normal (1); Weibull (2)

The events have been categorized into three main groups: patient flow events (relating to patient movement through the system), operational events (relating to direct care delivery), and support events (relating to auxiliary activities). This classification provides

a clearer understanding of how different statistical distributions are applied to distinct aspects of healthcare operations. For example, while patient arrivals predominantly follow Poisson distributions, clinical process times show more variation in distribution choice, reflecting their greater complexity and variability.

4.4.1. Patient Arrival Patterns

Patient arrival patterns vary significantly between scheduled and unscheduled care settings. In emergency departments, the Poisson distribution is widely used to model patient arrivals, particularly in high-volume settings. This aligns with Bhattacharjee and Ray [48], who demonstrated that Poisson distributions effectively capture the randomness of emergency arrivals while ensuring computational efficiency.

In outpatient settings, Harper and Shahani [49] found that a Normal distribution more accurately represents scheduled patient arrivals, especially when accounting for variations in punctuality. Their study showed that combining Normal distributions for scheduled patients with exponential distributions for walk-ins improved model accuracy by 18% compared to using a single distribution.

While certain distributions are commonly applied, their suitability must be empirically validated for each specific healthcare setting. Bhattacharjee and Ray [47] emphasize the importance of statistical testing and real-world data analysis to ensure that the chosen distribution accurately reflects the observed arrival patterns, optimizing model reliability.

4.4.2. Length of Stay and Process Times

Length of stay (LOS) modeling shows greater complexity in distribution selection. Kolker [50] demonstrated that lognormal distributions effectively capture the right-skewed nature of emergency department LOS patterns. Their analysis of over 15,000 patient visits revealed that lognormal distributions provided the best fit for ED LOS data ($p < 0.05$ in Kolmogorov–Smirnov tests).

Studies by Almashrafi and Vanderbloemen [51] in surgical units found the following:

- General surgery: Weibull distribution best fitted post-operative stays.
- Orthopedic procedures: Gamma distribution showed superior fit.
- Day surgery: Triangular distribution adequately represented shorter stays.

4.4.3. Service and Activity Times

Service time modeling varies significantly by activity type. Lakshmi and Iyer [52] found the following:

- Clinical consultations: Triangular distributions proved effective.
- Diagnostic procedures: Beta distributions showed better fit.
- Administrative tasks: Normal distributions adequately captured routine tasks.

Their comprehensive analysis of 2500 service interactions demonstrated the importance of context-specific distribution selection.

4.4.4. Validation and Selection Criteria

Our review revealed inconsistencies in distribution validation approaches. Following best practices identified by Gul and Guneri [53], we recommend the following statistical tests: the Kolmogorov–Smirnov test for continuous distributions, the Chi-square test for discrete distributions, and the Anderson-Darling test for tail-sensitive distributions. For visual analysis, we suggest Q-Q plots to assess distribution shape, P-P plots for cumulative probability comparison, and histogram overlays for direct distribution comparisons.

4.4.5. Impact on Model Accuracy

Recent research by Demir et al. [54] has quantified the impact of distribution selection on model accuracy. Their comparative analysis of Emergency Department (ED) patient flow models revealed that selecting an appropriate distribution reduces prediction errors by 23%. Moreover, combining multiple distributional approaches enhances model accuracy by 31%, while empirical distribution fitting outperforms theoretical distributions in modeling complex processes.

4.5. Technological Evolution of DES in Healthcare

The integration of emerging technologies has transformed healthcare discrete event simulation (DES) from standalone modeling tools into sophisticated decision support systems. Our analysis highlights a progressive shift toward data-driven, interconnected simulation environments that enhance both model accuracy and practical applicability.

4.5.1. Artificial Intelligence Integration

Recent advancements in AI have significantly improved DES applications. Lamé et al. [55] demonstrated that machine learning algorithms enhance prediction accuracy for patient arrivals, dynamically adjust service time distributions, and automate pattern recognition in patient flow. Moreover, AI-driven models enable real-time optimization of resource allocation, leading to more adaptive and responsive healthcare simulations. Their study in an emergency department setting showed that integrating machine learning improved waiting time predictions by 24% compared to traditional statistical approaches.

4.5.2. IoT Integration and Real-Time Data Collection

The adoption of Internet of Things (IoT) devices has revolutionized data collection in healthcare DES models. Tian et al. [56] demonstrated how IoT-enabled healthcare environments facilitate automated patient tracking and real-time monitoring of resource utilization in their comprehensive review of healthcare information systems. Supporting this evolution, Yang et al. [57] provided evidence that integrating IoT with healthcare simulations enhances data collection accuracy and enables real-time model updates.

4.5.3. Digital Twin Development

The concept of digital twins has emerged as a transformative advancement in healthcare DES. Barricelli et al. [58] provide a comprehensive review of digital twin applications, demonstrating their role in enabling continuous system monitoring and real-time decision support. Their analysis highlights the potential of digital twins for healthcare process optimization and resource management. Fuller et al. [59] further demonstrated the practical application of digital twins in healthcare settings, particularly in improving operational efficiency and resource utilization.

4.5.4. Impact on Healthcare Operations

The integration of these technologies has demonstrated significant improvements in healthcare delivery efficiency and operational performance. Bradley et al. [60] conducted a comprehensive analysis of technology-enhanced DES implementations across multiple healthcare facilities, documenting substantial improvements in operational metrics. Their study demonstrated that integrated simulation approaches led to significant reductions in patient waiting times, enhanced resource utilization, and improved model accuracy. These findings underscore the transformative potential of technology-enhanced DES in healthcare settings, particularly when multiple technologies are integrated cohesively to support operational decision-making.

4.5.5. Implementation Challenges

Despite these advancements, several challenges remain in implementing advanced DES technologies in healthcare. Through their analysis of healthcare simulation implementations, Brailsford et al. [61] identified key barriers including data security concerns, integration with legacy systems, and the need for extensive staff training. Marshall et al. [62] further emphasized that successful implementation requires a phased approach that aligns with existing infrastructure and regulatory requirements.

4.6. Implications for DES Implementation in Healthcare Organizations

Our systematic review identifies key factors influencing the successful implementation of DES in healthcare organizations. Case studies reveal that institutions carefully consider both technical infrastructure and organizational factors when adopting DES solutions.

From a technical perspective, integration with existing hospital information systems, computational resources, network infrastructure, and data storage capabilities play a fundamental role in ensuring a seamless implementation. Equally important are organizational factors, such as staff expertise, resource availability, stakeholder engagement, and project timelines. Institutions that prioritized structured training programs and cross-departmental collaboration strategies often reported smoother transitions and higher adoption rates.

A common approach among successful implementations involved phased rollouts, beginning with pilot projects before scaling to broader applications. Additionally, robust data collection and validation procedures emerged as critical elements, with organizations that established strong data foundations experiencing more reliable model outcomes. This observation aligns with the findings of Katsaliaki and Mustafee [5], who emphasized the importance of data quality in simulation success.

Furthermore, stakeholder engagement proved to be a decisive factor across multiple studies. Hospitals that actively involved clinical staff in the simulation development process reported greater acceptance and practical utilization of DES tools, as documented by Mohiuddin et al. [39]. These findings underscore the necessity of a multidisciplinary approach, where both technical and human factors are addressed to maximize the impact of DES in healthcare settings.

4.7. Limitations

This review focuses on 616 publications related to discrete event simulation from 2010 to 2022. It is important to note that the included publications were sourced on the PubMed, Scopus, and WOS databases. Consequently, articles from the gray literature, which is commonly found in the healthcare sector due to privacy concerns, were not included in this analysis.

Furthermore, this review provides a broad comparison of the benefits of DES software in the healthcare sector and the reported results by authors during the 12-year period. However, it is worth mentioning that this study did not consider the implementation costs associated with the models.

One limitation of this study is the potential generalization of the findings from the specific distributions used to other healthcare procedures. It is important to acknowledge that certain statistics and results may not be applicable or hold true for all medical departments. Each department may have unique operational challenges and factors that were not extensively examined in this study.

4.8. Literature Gap and Future Research

Discrete event simulation offers a wide range of benefits for enhancing hospital processes, encompassing patient care and logistics.

This systematic literature review aimed to identify knowledge gaps in the existing global research on DES. Data were extracted from PubMed, Scopus, and WOS databases using the PRISMA search method. The analysis revealed that the reviewed systematic reviews lacked specific information on the following:

- The software utilized in the analyzed case studies.
- The medical services where discrete events were applied.
- The statistical distributions employed for modeling discrete event times.

This article addresses these knowledge gaps by exploring these aspects, contributing to a more comprehensive understanding of DES implementation in healthcare settings.

As a suggestion for future research, it is recommended to continue collecting such information on a biannual basis to support scientific studies on the implementation of DES within the hospital sector. This ongoing data collection can further enhance and enrich research related to DES in healthcare settings.

5. Conclusions

This systematic review of 616 publications, including 349 case studies, reveals significant patterns in the implementation and evolution of discrete event simulation (DES) in healthcare settings between 2010 and 2022. Our analysis yielded three key findings:

First, the application of DES in healthcare demonstrates distinct evolutionary phases, progressing from basic process modeling to sophisticated, technology-integrated solutions. This evolution is particularly evident in the increasing complexity of models and their integration with hospital information systems. The COVID-19 pandemic accelerated this evolution, spurring rapid adoption of advanced modeling approaches and real-time optimization capabilities.

Second, our analysis of statistical distributions in DES implementations reveals context-specific patterns in distribution selection. While certain distributions show a better fit for particular applications (e.g., Poisson for ED arrivals, lognormal for length of stay), successful implementation requires careful validation within each specific healthcare context. This finding emphasizes the importance of rigorous statistical testing and data validation in DES model development.

Third, the geographical analysis shows a concentration of DES applications in developed healthcare systems, particularly in the USA, UK, and Canada, while revealing an increasing trend of adoption in emerging healthcare markets. This pattern suggests both the maturity of DES applications in established systems and growing recognition of its value in developing healthcare environments.

Given these findings, and acknowledging the challenges identified in our review, we propose four key implementation strategies to enhance DES adoption and effectiveness in healthcare organizations:

1. Implementation Approach (addressing evolutionary phases)
    - Begin with well-defined, high-impact departments where data collection is feasible.
    - Establish clear success metrics before implementation.
    - Develop pilot projects before full-scale deployment.
    - Ensure stakeholder engagement throughout the process.
2. Model Development (addressing statistical validation needs)
    - Select appropriate statistical distributions based on empirical data analysis.
    - Validate models using multiple approaches (statistical testing, stakeholder verification).
    - Document all assumptions and limitations clearly.
    - Plan for regular model updates and refinements.

3. Technical Integration (addressing technological evolution)
    - Assess existing IT infrastructure capabilities before implementation.
    - Implement data collection processes early in the project.
    - Ensure compatibility with hospital information systems.
    - Plan for scalability in future expansions.
4. Organizational Considerations (addressing adoption patterns)
    - Invest in staff training and development.
    - Establish clear communication channels among stakeholders.
    - Create standard operating procedures for model maintenance.
    - Monitor and document improvements systematically.

However, several significant challenges remain in healthcare DES implementation:

- Interoperability: Integration with diverse hospital information systems remains complex.
- Data Quality: Ensuring consistent, high-quality data collection across departments.
- Organizational Resistance: Overcoming resistance to change and new technological adoption.
- Resource Constraints: Addressing implementation costs and training requirements.
- Standardization: Lack of standardized validation methodologies across healthcare settings.
- Scalability: Challenges in scaling successful pilot projects to full implementation.

Future research should focus on addressing these challenges while expanding DES applications in resource-limited settings and emerging healthcare markets. Particular attention should be paid to developing standardized validation methodologies, improving system integration capabilities, and creating frameworks for sustainable implementation in diverse healthcare environments.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app15041861/s1, Supplementary Materials Annex S1.

Author Contributions: Conceptualization, D.V.M. and A.M.G.M.; methodology, D.V.M. and A.M.G.M.; software, C.B.F.; validation, D.V.M., C.B.F. and A.M.G.M.; formal analysis, D.V.M.; investigation, D.V.M. and C.B.F.; resources, D.V.M. and C.B.F.; data curation, D.V.M., C.B.F. and A.M.G.M.; writing—original draft preparation, D.V.M. and C.B.F.; writing—review and editing, D.V.M. and C.B.F.; visualization, C.B.F.; supervision, A.M.G.M.; project administration, D.V.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article and Supplementary Materials. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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