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Faculty of Business Economics

Master of Management

Master's thesis

Adherence of business process simulation literature to the STRESS guidelines

Dickson Akinnawo

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :

Prof. dr. Niels MARTIN



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Abstract

This paper examines the extent to which business process simulation (BPS) case studies adhered to the STRESS (Strengthening the Reporting of Empirical Simulation Studies) guidelines, introduced to strengthen transparency and reproducibility in the simulation research community. The literature review used a total of 62 BPS case studies published in various journals and conference proceedings between 2019 and 2024. Each case study was evaluated using a 20-item checklist derived from the STRESS guidelines across the three simulation paradigms: Discrete-Event Simulation (DES), Agent-Based Simulation (ABS), and System Dynamics (SD). The findings indicated that reporting of simulation objectives and model-building logic (e.g purpose of the model, basic model logic, etc) was generally well-explained, but there were significant issues with reporting the implementation section of the guidelines (e.g., random sampling for consideration of uncertainty, model execution, and notably, lack of sharing the model code). Although the average adherence score varied across the three paradigms, the different journals and/or proceedings and the year, there were similarities in the pattern of adherence to most of the STRESS guidelines. The study highlighted the need for the BPS reporting community to focus on strengthening standardised reporting guidelines and open science research practices in order to improve reproducibility.

Keywords: Business Process Simulation (BPS), STRESS guidelines, Discrete-Event Simulation, Agent-Based Simulation, System Dynamics

1 Introduction

Business Process Simulation (BPS) refers to mimicking the behaviour of business processes using a simulation model (Melao & Pidd, 2003). BPS is a safe and controlled way to evaluate business processes, especially when the real-world evaluation is infeasible, too expensive and/or too risky. Robinson et al. (2004) indicated that simulation can help facilitate understanding, diagnosis, and improvement of complex systems because analysts can model systems and play "what if" scenarios without disrupting real operations. Organisations can use simulations to examine the potential outcomes of different decisions or to measure key performance indicators like cycle time, resource utilisation, and the level of missed or delayed tasks. Using a simulation can help organisations make more informed and effective decisions related to business process management (Dumas et al., 2018).

There are three key simulation paradigms that can be used to model different types of systems: Discrete-Event Simulation (DES), Agent-Based Simulation (ABS), and System Dynamics (SD) (Dehghani et al., 2017; Günel & Pidd, 2010). DES is utilized for modelling queuing systems, which happen when entities arrive at a rate faster than their processing capacity in the next activity. It can be used in various systems, whether it is physical objects, people, or information represented by entities flowing through the system (Robinson, 2014). Conversely, ABS models are based on individual agents with distinct rules that define their behaviours and interactions between the agents. As a result of the provided (and often complicated) rules, various behaviour patterns can come up from the interactions of the agents (Giabbanelli et al., 2021). SD is a systems method, where the various elements of a system are thought of as stocks, flows and supplementary variables with feedback between them (Lane, 2000).

In previous years, major concerns have been raised about the reproducibility of research findings in simulation research and their benefits (Uhrmacher et al., 2016; Yilmaz et al., 2014). In the context of simulation modelling, reproducibility has several scientific, societal and practical benefits. First, reproducibility allows researchers to reuse a simulation model to investigate additional hypotheses within the same domain or to evaluate the applica-

bility of an effective operational strategy in another context. Second, it enables the reuse of underlying knowledge or components from an existing model to address similar problems, as building a simulation model from scratch can be expensive. Third, reproducibility facilitates the reuse of data, particularly in situations where data is scarce or unavailable. Sharing this data publicly enables future modelling studies to utilise these values, thus enhancing the validity of the developed models. Finally, it aids in validating new output analysis techniques, computational procedures, or simulation optimisation methods by providing a controlled setting that allows these techniques to be evaluated and their performance assessed (Monks et al., 2018; Robinson et al., 2004). Reproducibility is crucial for scientific progress, with no exception to simulation-based research. Research results can only be confirmed when they are independently reproducible by different scholars, enabling them to validate and build on each other's work (Laine et al., 2007).

Reproducibility in simulation research is not only determined by the accuracy of the computational methods but also by broader methodological practices. Researchers have also pointed out the role of factors such as transparency in the model-building process, clearly stating the underlying assumptions, and the ability to replicate analytical processes are important for ensuring reproducible results (Williams et al., 2024). The concerns about lack of transparency, inadequate reporting of the assumptions made in simulation models, and the challenges associated with replicating results have raised serious issues with respect to reproducibility in simulation research. To tackle these challenges, Monks et al. (2018) created the STRESS (Strengthening the Reporting of Empirical Simulation Studies) guidelines for improved reporting and reproducibility in simulation studies. These guidelines are aimed specifically at models used in ABS, DES, and SD to improve their reproducibility (Monks et al., 2018). The STRESS guidelines consist of 20 checklist items that guide authors in documenting applied simulation studies and ensuring that all essential details are covered. Establishing these reporting guidelines will enhance research transparency by defining clear expectations regarding included details and where they can be found, thereby supporting reproducibility in simulation research (Williams et al., 2024).

Despite the potential benefits of the STRESS guidelines for improving reproducibility in simulation studies, there has been a paucity of information on the extent to which the STRESS guidelines have been adhered to since their publication in 2018. This research is important to understand the level of compliance with the STRESS guidelines to assess their usage in the simulation research community and identify areas where more of its implementation may be needed. Against this background, this paper investigates the extent to which the STRESS guidelines are adhered to in the business process simulation literature. This study examines case studies published between 2019 to 2024, and adherence was assessed by evaluating each case study against the STRESS guidelines. This paper aims to contribute to the research community by examining how consistently articles have adhered to reporting guidelines over the years.

The remainder of the paper is structured as follows. Section 2 provides a background to the challenges of reporting in BPS and the existing guidelines in BPS. Section 3 outlines the methodology details to retrieve articles for analysis. The results of the evaluation and analysis are reported in Section 4. The paper ends with a discussion of research findings in Section 5 and a conclusion in Section 6.

2 Background

This section provides background information on the challenges of reporting in BPS and the existing guidelines in BPS. Section 2.1 focuses on the challenges to reproducibility in BPS studies, while Section 2.2 discusses the existing reporting practices, their weaknesses, and highlights the importance of STRESS guidelines in reporting.

2.1 Challenges to Reproducibility in Business Process Simulation Studies

Simulation studies need to be conducted with the same rigour as any other experimental study in order to yield valid and reproducible results (Boomsma, 2013; Burton et al., 2006; Hallgren, 2013). However, the lack of proper documentation and transparency in published simulation studies creates difficulties for both study reproduction and evaluation of credibility and methodological soundness (Burton et al., 2006; Feinberg & Rubright, 2016; Waltemath et al., 2011). This section identifies four key challenges which commonly affect reproducibility in BPS studies.

Firstly, the lack of proper documentation about simulation design and process makes it difficult to reproduce the results (Fitzpatrick, 2019; Monks et al., 2018; Navarro et al., 2018; Zhang & Robinson, 2021). Simulation studies consist of three main elements, which include conceptual models (the abstract framework), the computational model (the coded implementation) and the simulation experiment (conditions and parameters). The absence of crucial details about conceptual models, computational implementations and experimental conditions in studies is

a common problem. Lack of a comprehensive description of data assumptions, logic, and scope will lead to misinterpretation of the intended mechanisms or mathematical relationships. Also, discrepancies between the different layers of a simulation study, such as the conceptual model, the implemented code, and the published results, can affect reproducibility. For instance, the code may not match the conceptual model, or the published results may not align with either of the two layers. Furthermore, these differences can lead to different implementation approaches and hinder replications of the study (Fitzpatrick, 2019; Zhang & Robinson, 2021).

Secondly, to ensure the reproducibility of stochastic simulation models, it is essential to report the full details of the experimental setup. These details should include methods used for random seed generation, replication strategies, and variability controls (Williams et al., 2024; Zhang & Robinson, 2021). Without this detail, the result may become sensitive to small changes in the way that the simulation is executed. Inadequate reporting decreases the transparency and makes it difficult for other researchers to reproduce the results reliably.

Thirdly, failure to provide traceable sources of referenced materials prevents reproducibility of the results. Simulation research studies often reference background models, datasets and algorithms which exist in unpublished, proprietary, or inaccessible to the public (Monks et al., 2018). Sharing source code might improve transparency, although it is sometimes not enough. Reproducibility may still be affected due to implementation problems, outdated software dependencies, or undocumented assumptions present in the code (Antunes & Hill, 2024; Blinov et al., 2021).

Lastly, technical variability across software platforms, programming languages, and execution environments produces different results (Antunes & Hill, 2024; Chen et al., 2019; Donkin et al., 2017). The difference between numerical algorithms or random number generators across platforms may generate substantial output variations, which makes reproduction difficult, even with complete access to code and data.

The simulation research community has developed several guidelines, which will be discussed in the next section, to address some of these challenges. These guidelines recommend that studies should clearly state their objectives, explain model assumptions and logic, define the process of random number generation, (Ring et al., 2005; Sawatzky et al., 2017), specify software and version used (Boomsma, 2013; Paxton et al., 2001), and document essential design parameters, such as sample size and number of replications (Burton et al., 2006; Feinberg & Rubright, 2016; Skrondal, 2000). The purpose of these guidelines is to improve the reproducibility of simulation models through standardized, transparent practices for model development and analysis.

2.2 Existing Reporting Guidelines in Business Process Simulation

Several reporting guidelines exist with the primary aim of enhancing transparency, thus contributing to improving reproducibility in simulation studies, but they differ substantially regarding their scope, structural design, and practical application. Monks et al. (2018) states that the Overview, Design concepts, and Details (ODD) protocol, which Grimm et al. (2006, 2010) created, serves as a primary guideline for agent-based modelling in ecological fields. The ODD protocol provides researchers with a structured descriptive guideline to explain model components and behaviours through standardized documentation. The primary focus on the ecological field restricts the immediate application of ODD to business processes or discrete-event simulations.

In contrast, the Minimum Information About a Simulation Experiment (MIASE) guidelines, introduced by Waltemath et al. (2011), were designed to enhance reproducibility in computational biology. The guidelines provide essential documentation requirements for simulation experiments (model versions, simulation procedures and analysis methods); however, they lack detailed step-by-step implementation guidelines for simulation tailored to other domains such as BPS. MIASE does not provide modelling guidelines, experimental design, and reporting standards used in BPS, which makes it too general to be useful for reproducibility outside its original context.

The MMRR (Model, Method, Results, and Replicability) guideline, developed by Rahmandad and Sterman (2012), provides support for transparent simulation study reporting through its four core elements, which include model formulation, methodological rigour, result reporting and replication conditions. However, the guideline exists mainly within SD and lacks a clear checklist format, which makes it less practical for use across different simulation paradigms, including ABS and DES.

These guidelines differ from each other in terms of their simulation paradigm targets as well as their complexity level and implementation simplicity. The simulation reporting standards demonstrate essential progress toward standardisation, yet their specific domains and varying levels of detail create obstacles for widespread adoption. For instance, the ODD protocol is appropriate for ABS but is not flexible enough for different simulation paradigms such as DES or SD. This variation has posed a barrier to establishing a uniform standard throughout the broader simulation community.

To address the challenges with reproducibility with the guidelines discussed above, Monks et al. (2018) introduced the STRESS (Strengthening the Reporting of Empirical Simulation Studies) guidelines. The STRESS guidelines were created to improve both the quality and transparency of reporting, specifically for BPS studies. Unlike earlier reporting guidelines, the STRESS guidelines extend beyond the computational models to cover the entire simulation study process, including the conceptual model, experimental design, data sources, implementation and result analysis. The aim of these guidelines is to provide enough detail about the model and study processes for reproducibility and critical assessments. Unlike other guidelines that are often paradigm-specific or limited in their details to reproduce an entire study, the STRESS guidelines are more comprehensive, systematic and useful for promoting transparency and reproducibility in BPS.

The STRESS guidelines were created based on (1) a comprehensive review of good practice reporting methods within Operational Research and Management Science (ORMS) and software engineering; (2) input from the modelling & simulation community, and (3) evaluation by experts (Taylor et al., 2017). The guidelines are organised into six main sections: objectives, model logic, data, experimentation, implementation, and code access. Overall, STRESS includes a checklist of 20 items (Table 1).

The STRESS guidelines have three specific variants, which are STRESS-ABS (Agent-Based Simulation), STRESS-DES (Discrete-Event Simulation), and STRESS-SD (System Dynamics). These versions of the STRESS guideline extend the general STRESS guideline by adapting the checklist items to reflect the methodological and structural characteristics unique to each simulation type. For example, STRESS-ABS includes items relevant to agent interactions and behaviours, STRESS-DES emphasises process flow and queuing logic, while STRESS-SD focuses on feedback loops and stock-flow structures. All versions share the core reporting principles of the general STRESS guideline, but the paradigm-specific checklists provide more targeted guidance, making them more effective for promoting reproducibility within each modelling approach. The full checklists for each version are available in Appendices A through C.

Table 1: **STRESS Guidelines Checklist Criteria by Monks et al. (2018)**

Sections	Items	Guidelines	Criteria
Objectives	1.1	Purpose of the model	Explain the background and rationale for the model.
	1.2	Model outputs	State the qualitative or quantitative system level outputs that emerge.
	1.3	Experimentation aims	Provide specific information about how the model is being used to achieve the stated purpose.
Logic	2.1	Base model overview diagram	Provide state chart, process flow or equivalent diagrams to describe the basic logic of the base model to readers
	2.2	Base model logic	Give details of the base model logic (a simplified explanation of the complex association).
	2.3	Scenario logic	Give details of any difference in the model logic between the base case model and scenarios.
	2.4	Algorithms	Provide further detail on any algorithms in the model that mimic complex or manual processes in the real world.
	2.5	Components	Give the basic conceptual building blocks of the model (Entities, activities, resources, stocks/levels, interaction typology entry/exit points etc.)
Data	3.1	Data sources	List and detail all data sources
	3.2	Input parameters	List all input parameters in the model, providing a description of each parameter and the values used

	3.3	Pre-processing	Provide details of any data manipulation or filtering that has taken place before its use in the simulation
	3.4	Assumptions	State and justify the assumptions used to set input parameter values and distributions
Experimentation	4.1	Initialisation	State if a warm-up period, initial agent and environment has been used, its length and the analysis method used to select it.
	4.2	Run length	Detail the run length of the simulation model and time units.
	4.3	Estimation approach	State if the model is deterministic or stochastic
Implementation	5.1	Software or programming language	State the operating system and version and build number
	5.2	Random sampling	State the algorithm or package used to generate random samples within the software/programming language used
	5.3	Model execution	If the model has a time component, describe how time is modelled
	5.4	System specification	State the model run time and specification of hardware used
Code access	6.1	Computer model sharing statement	Provide statement or link to model code

3 Methodology

This study assesses the extent to which BPS case study articles adhered to the STRESS guidelines. An evaluation of reporting practices was conducted through a structured selection of relevant case studies from the literature.

Section 3.1 outlines the process for searching and selecting case studies. Subsequently, Section 3.2 describes the data extraction and analysis approach used to assess the extent to which the literature adheres to the STRESS guidelines.

3.1 Case Study Search & Selection

This section is split into two parts; Section 3.1.1 focuses on searching for relevant articles while Section 3.1.2 describes the selection process.

3.1.1 Case Study Search

To identify relevant articles for this review, a search strategy was used. Keywords were selected based on the core concepts of the research objective: simulation paradigms and case study applications. These concepts were derived from a preliminary review of the literature and the terminology commonly used in simulation reporting. Boolean logic was then used to combine these keywords to form comprehensive search strings, enabling the identification of studies that specifically focus on the application of simulation in business process case studies. The specific keywords used included the combinations of terms: ("case study") AND ("simulation" OR "discrete event simulation" OR "agent-based simulation" OR "system dynamics").

Literature searches were then conducted in selected journals and conference proceedings that focused on business process simulation and organisational case studies to find articles that addressed the research question. This study focused on articles published in English between 2019 and 2024, with 2019 chosen as the cutoff year since the STRESS guidelines were introduced in 2018, thus allowing relevant studies from the subsequent year.

Thus, the selected journal and conference outlets are:

- Journal of Simulation (JoS)
- Simulation Modelling Practice and Theory (SMPT)
- Simulation
- Winter Simulation Conference (WSC)

These outlets were chosen based on their established track record of publishing simulation research with respect to methodological innovations as well as applied work in business process simulation. Further justification of this inclusion is that the Winter Simulation Conference is known for its long-standing history and recognition within the simulation research community as a means for presenting progress in the field.

3.1.2 Case Study Selection

The purpose of the case study selection was to identify articles relevant to BPS. To achieve this, the inclusion and exclusion criteria were first established.

Inclusion criteria:

- INC 1: The paper must be centred on simulation in an organizational context
- INC 2: The paper must cover at least one of these simulation fields: discrete-event simulation, agent-based modelling, or system dynamics

Exclusion criteria:

- EX 1: The paper is not written in English.
- EX 2: The full text of the paper is not accessible.
- EX 3: The paper is not a case study in an organizational setting.

These criteria were first applied to the titles and abstracts of the articles found through searches. Articles that passed these checks were then evaluated through a full-text examination to confirm their suitability for inclusion in the analysis.

Full-text screening is the last stage of the case study search and selection process. During this stage, the full text of all articles that passed the initial screening was retrieved and reviewed according to the inclusion and exclusion criteria. After this assessment, the final selection was made, identifying the papers that satisfied the criteria for data extraction and analysis.

3.2 Data Extraction & Analysis

A structured data extraction process was applied. The first step involved collecting basic information from each paper, which included the title and year of publication, journal or conference name, simulation paradigm, and author affiliations.

Each paper was critically assessed on the extent to which it applies each of the 20 STRESS guideline items. Each item of the guideline was evaluated according to its compliance with the defined criteria (see Appendix A, B, C for the defined criteria developed by (Monks et al., 2018)). Given the potential for incomplete compliance with the reporting of some STRESS criteria, each item of the guidelines was assessed and classified into three categories: Fully adhered, Partially adhered and Not adhered.

- Fully adhered: The criteria outlined in the guideline are adhered to completely.
- Partially adhered: Some aspects of the criteria of the guideline are addressed while others are missing, or insufficiently detailed.
- Not adhered: There is no adherence to the guideline.

3.2.1 STRESS Guidelines Adherence

Each item of the guideline was evaluated according to its level of adherence and scored based on the classification.

- Fully adhered = 1
- Partially adhered = 0.5
- Not adhered = 0

The scoring system provided a standardised method to evaluate how well each study followed the STRESS checklist during the simulation process reporting. It helps to identify both the total reporting adherence and the specific patterns and gaps that exist between different studies and simulation approaches.

In addition to the scoring system, the frequency of adherence categories, including fully adhered, partially adhered and not adhered, was recorded for each checklist item throughout all papers. The frequencies were expressed as percentages to demonstrate the prevalence of each adherence level.

The STRESS guidelines adherence level was quantified through an adherence score calculation that used the following formula:

$$\text{Adherence Score (\%)} = (\sum \text{Score of each guideline items} / \text{Max possible score}) \times 100\%$$

To evaluate how well the selected papers adhered to the STRESS guidelines, each paper was analysed and summarised using several units of analysis. These included:

- **Case study assessment:** Each case study was assessed to determine the extent of adherence to the STRESS guidelines.
- **Guideline checklist items:** Each item of the guidelines was assessed to determine the extent of adherence of the case study to each item.
- **Simulation paradigm used:** (DES, ABM, and SD). This identified which simulation paradigms best adhered to the STRESS guideline.
- **Journal/Conference outlet:** The extent of adherence to STRESS guidelines for each journal or conference was evaluated.
- **Publication year:** The extent of adherence to STRESS guidelines from 2019 to 2024 was evaluated to assess advancements in the reporting of business simulation processes over time.

4 Results

The selection process for the case studies included in this review is shown in Figure 1. Four main publication outlets generated a total of 2,443 papers. During title and abstract screening, 2,279 records were excluded due to either not being in English, not being case studies, or not being conducted in an organisational context. Out of the 164 reports to be sought out for retrieval, 33 could not be accessed due to paywalls. The eligible 131 papers were screened for full-text validity, with 69 excluded for not meeting organisational context or case study standards. Finally, 62 studies met all decision criteria and were included in the final review for analysis (Appendix D).

The case study papers were further analysed on their adherence to the STRESS guidelines, focusing on publication outlets, publication years, simulation paradigms, and STRESS guideline items. The result is structured as follows: Section 4.1 provides a summary of the dataset, including the distribution of papers across simulation types, publication years, and outlets. Section 4.2 presents the overall adherence scores of individual case studies. Section 4.3 explores how frequently each STRESS checklist item is addressed across the sample. Section 4.4 compares adherence levels across different simulation paradigms (DES, ABS, SD), while Section 4.5 investigates variations in adherence based on journal or conference outlet. Finally, Section 4.6 analyses adherence level over time, from 2019 to 2024, to assess usage of the reporting guidelines in BPS studies.

4.1 Data Summary

After implementing the screening criteria, a total of 62 papers were selected for analysis. The proceedings of the Winter Simulation Conference produced the highest number of papers at 28, while other journal outlets published between 10 and 13 papers each (Figure 2). The majority of papers used DES as their simulation paradigm, with 39 papers, while ABS, SD, and hybrid approaches, which constitute at least two paradigms (SD-DES, ABS-SD, etc.), appeared in less than 10 papers (Figure 3). The number of selected case study articles published annually varied and ranged from 7 to 16 (Figure 4).

4.2 Adherence to the STRESS Guidelines

An analysis of adherence to the STRESS guidelines across the 62 case studies using the adherence scoring method described in the methodology section revealed significant differences in adherence between papers to the reporting guidelines (Figure 5). The adherence scores ranged from 25% to 90%, which indicates different levels of adherence to the reporting standard across the studies. Among the 62 papers, only 12 studies have a high adherence score of over 75%, indicating strong compliance with the STRESS criteria. For instance, a study by Sung et al. (2022) with an adherence score of 90% fully adhered to most of the STRESS guidelines criteria. In the objective section, the introduction clearly defined the simulation objective of optimizing mix of buses/chargers, the output which

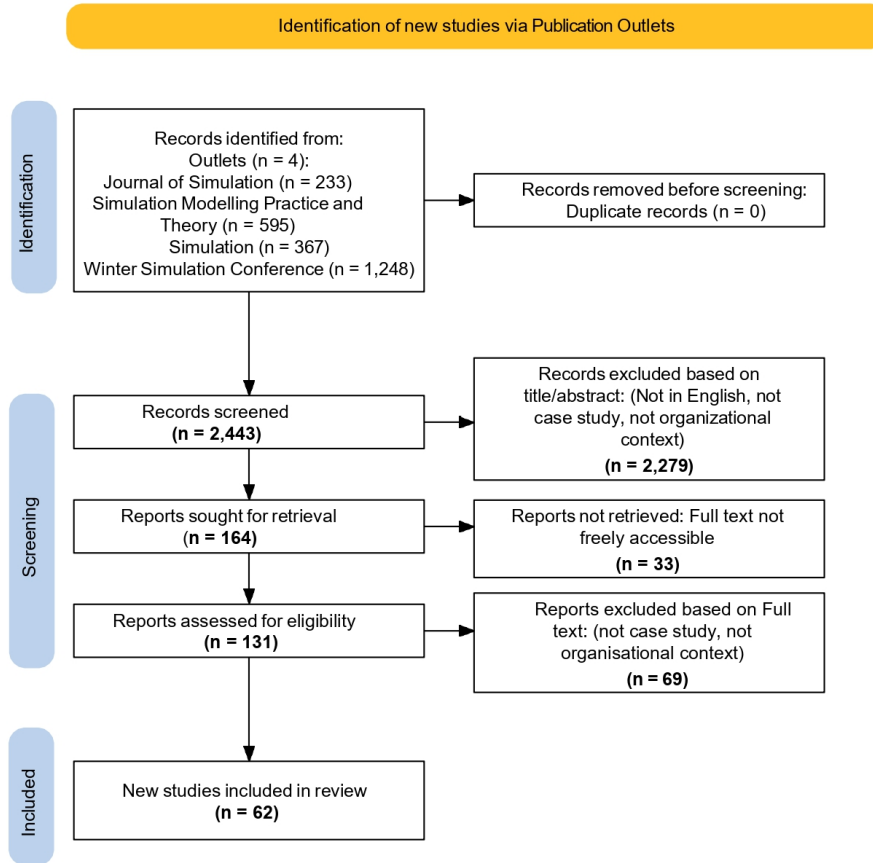


Figure 1: Prisma Flow Chart for Case Study Selection

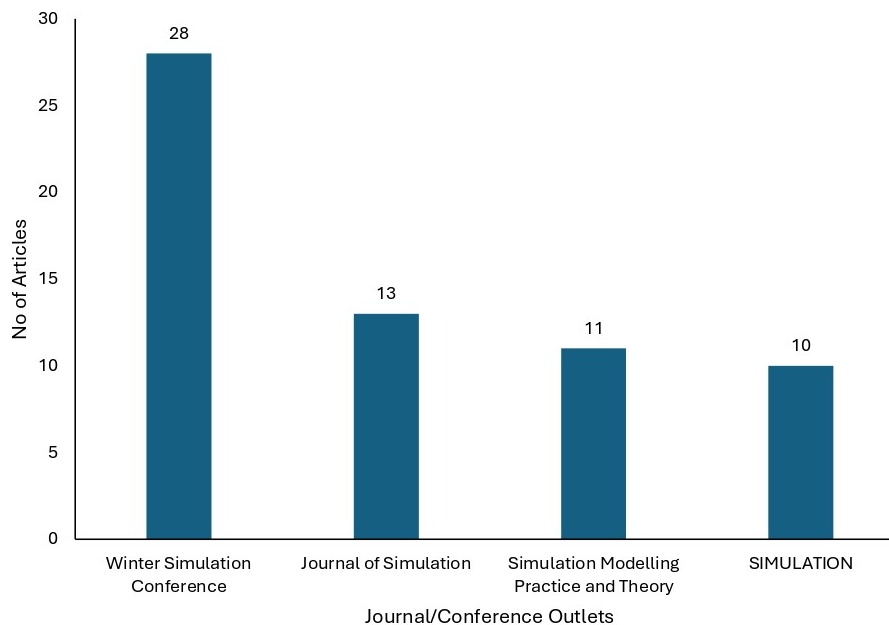


Figure 2: Summary of Journal/Conference Outlet Analysed

include cost components and scheduling metrics were stated and the experimentation were clearly stated which was a case-based experimentation with four scenarios tested and compared. The logic section was fully adhered to; the study clearly illustrates the DES procedures and logic in detail and with diagrams, the heuristic algorithm with pseudo-code was provided, and entities such as buses and chargers were described. Also in the Data Section, the data source, which was a real-world case (GDBus Taiwan), included input parameters such as routes, buses,

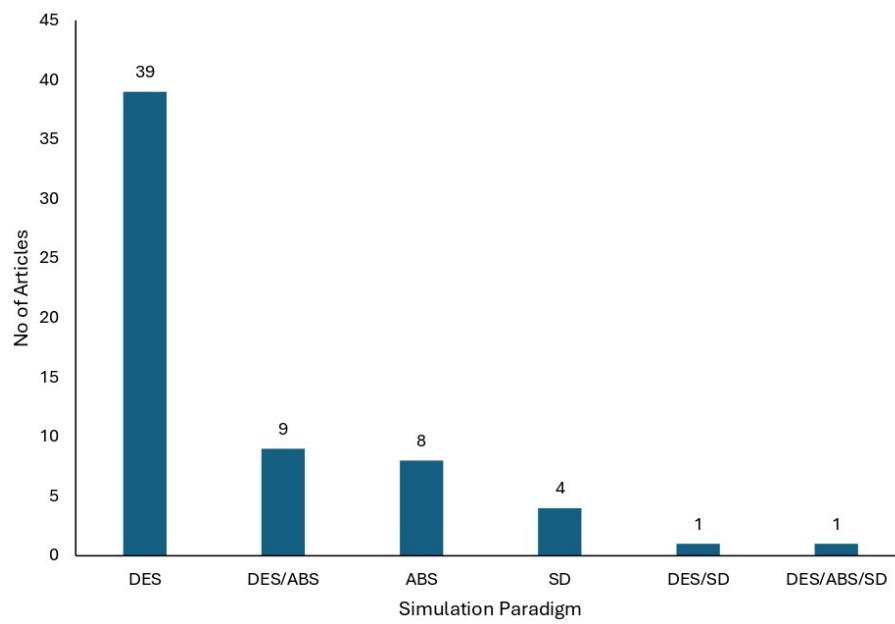


Figure 3: Summary of Simulation Paradigm Analysed

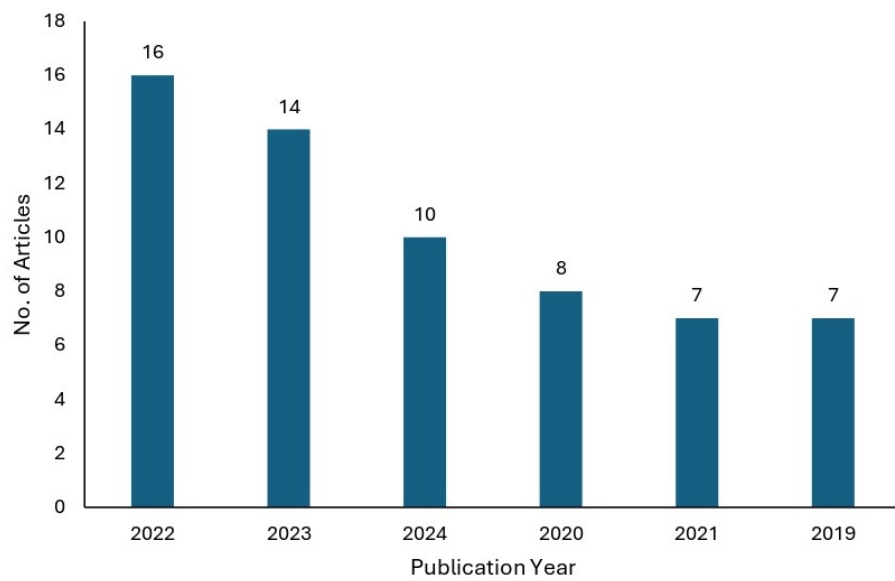


Figure 4: Summary of Publication Year Analysed

and chargers. Assumptions regarding the state of charge, charging compatibility and strategy rules were provided. However, there was no clear mention of the preprocessing steps taken.

The experimentation section was also fully adhered to, stating that the run length was a full day's bus schedule. Additionally, the estimation approach was described, which involved multiple runs compared with generic algorithms and random sampling. The implementation section fully complied with the STRESS guidelines; the software used was Python with the VBA^{Sim} library, and the system specifications were Windows 8.1 and an i7 CPU. However, there was no provision of a link or statement to access the simulation model's code.

A large proportion of studies (34) had adherence scores between 50% and 74%, indicating relatively comprehensive reporting, with few of the guidelines partially adhered to or not adhered to at all. These studies often provided information about simulation objectives and the general model structure; however, they lacked detail regarding data assumptions, experimentation, implementation specifics, and code access. For instance, the case study by Attar et al. (2023) achieved an adherence score of 73%. This study fully adhered to the objective section of the STRESS guidelines, clearly stating its goals: to increase throughput, reduce work in progress and optimise smart line control. The model outputs detailed in the study included throughput, work in progress, machine states and process time.

Furthermore, the study adhered fully to the logic section of the STRESS guidelines, providing a clear explanation of speed control, buffer thresholds, and production dynamics. It described activities such as depalletizing, filling, pasteurizing, etc., in detail. In the data section, there was partial adherence to the pre-processing requirements, as it only assumed fixed availability without providing sufficient detail on the pre-processing stage. However, full details were provided on the data source, which was from a real European beverage plant. The input parameters included speed levels, buffer thresholds, and the mean time to failure, with the assumption that machine reliability is fixed and buffer thresholds and control rules are based on practical constraints. In the experimentation section, while the study specified the simulation run time as an 8-hour shift, the adherence to initialisation was partial. It simulated one shift (8 hours) but did not mention warm-up periods or initial conditions, and failed to describe the estimation approach. The implementation section also exhibited partial adherence; although the software used (Siemens Plant Simulation and SimTalk scripting) was specified, there were no details on random sampling or system specification. While the execution flow was implied via SimTalk, the simulation mechanism was not discussed. Additionally, there was no reference to the availability of simulation code.

Conversely, 16 studies fell below the 50% adherence level, indicating a substantial gap in adherence to STRESS guidelines, as these studies did not adhere to most of the guideline items. The least adherence score was 25%, which was recorded in a study by Özkan et al. (2023). In that study, the sections on objective, logic and data were partially adhered to, while the sections on experimentation, implementation and code access were not followed at all. In the objective section, the purpose of the model was clearly stated: to improve operations and assess alternatives. However, while the model outputs were mentioned, no mathematical definitions or calculation timings were provided. The objective of analysing different scenarios was noted, but there was no detailed scenario rationale, optimisation or design of experiments described. In the logic section, the process flow for simulation was included, but it lacked comprehensive logical details. Although some scenarios were qualitatively discussed, the logical differences were not clearly presented. Additionally, no specific algorithms or pseudocode for complex processes were provided. Some activities, such as docking and cargo transfer, along with resources like docks, were discussed; however, the routing logic and resource usage per activity were not detailed. Furthermore, in the data section, real terminal data were mentioned, but sources, sizes and data ranges were not specified. Some high-level assumptions were implicit but not explicitly described. Additionally, there was no mention of data pre-processing steps or input parameter values.

4.3 Adherence to STRESS Guideline Checklist Items

An evaluation of the selected case studies was conducted to assess their adherence to each specific checklist item of the STRESS guideline (STRESS-DES, STRESS-ABS & STRESS-SD). The adherence to the sections of the guidelines (Fully adhered, Partially adhered and Not adhered) is presented in Figure 6. "Partially adhered" indicates that while some key elements were reported, essential details were not fully addressed. For instance, in the study by Fabri et al. (2022), the components item was partially adhered to, although information about entities or activities was mentioned, other essential elements, such as resources, queues, and entry/exit points, were left out or not discussed in detail. Similarly, the data sources item was partially adhered to in the study by Mousavi et al. (2019). While the data sources were provided, the study lacked information on sample size, time frame, or data collection methods. Input parameter values were provided, but there was no justification for whether they applied to the base case or specific experiments. Furthermore, in the study by Jen et al. (2022), there was partial adherence to the initialisation item. The starting conditions were described, but there were insufficient details regarding whether they were deterministic or stochastic, and the warm-up periods were not adequately explained. Finally, the study

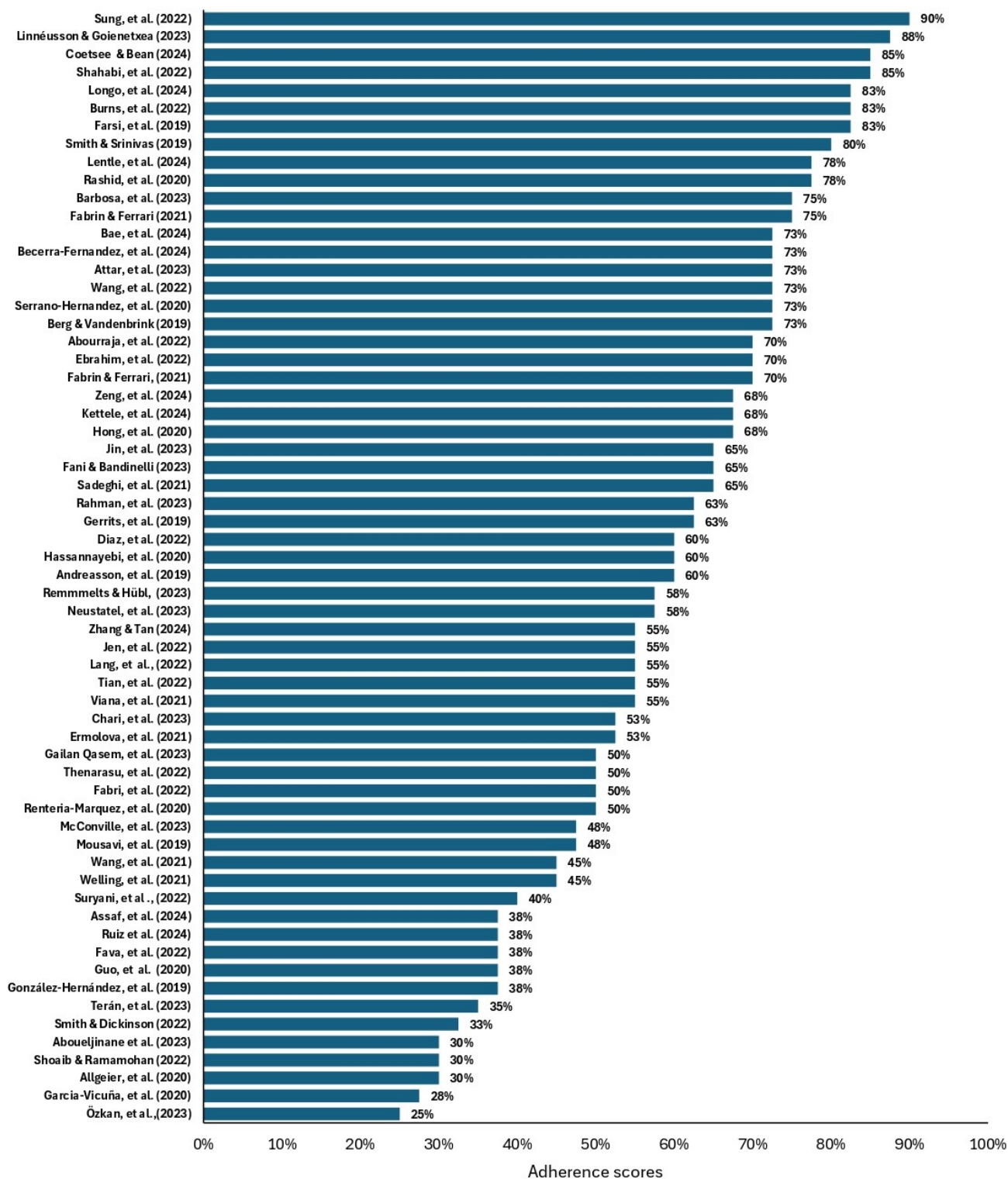


Figure 5: Adherence of case studies to STRESS guideline checklist items

by Ebrahim et al. (2022) did not adequately describe the model execution regarding the simulation's time structure, update order, or computing setup.

The analysis revealed that certain STRESS guidelines items, including purpose, experimentation aims, base model overview diagram and base model logic, were consistently well reported across the studies. Over 80% of the reviewed studies fully adhered to these items. For instance, studies conducted by Jen et al. (2022), Lang et al. (2022), and Serrano-Hernandez et al. (2020) demonstrated full adherence to the purpose, experimentation aims, base model overview diagram, and base model logic. In contrast, studies by Fava et al. (2022) and Garcia-Vicuña et al. (2020) did not fully comply to the experimentation aims, base model overview diagram and base model logic. These items are important for understanding the structure and intent of the simulation, and their absence hinders other researchers' ability to interpret, replicate and build upon the work. Additionally, other items such as model outputs, scenario logic, data sources, assumptions, run length and software or programming used were reported moderately in the research studies, with the adherence rate ranging from 55% to 76%.

In contrast, some technical details, which are in the data and implementation section of the STRESS guideline, such as algorithms, components, data sources, input parameters, and assumptions, were often only partially addressed. For instance, 35% to 56% of the studies only partially described the input parameters, data sources, components used, and the assumptions underlying the model structure and algorithms implemented. In the study conducted by Diaz et al. (2022), there was mention of recovery strategies like dynamic reorder policy; However, no pseudocode or specific algorithm details were provided. While parameter types (e.g., lead time, order size) were discussed, there are no detailed tables, distributions, or empirical values included. Furthermore, some assumptions, such as customer demand being constant, were inferred rather than formally stated.

Additionally, there was inadequate adherence to technical implementation details such as random sampling, model execution and system specifications. Less than 20% of studies fully address these items. For instance, in a study conducted by Lang et al. (2022), the paper does not provide any information about the random number generation method used for controlled experimentation, nor does it include information about the hardware, run times, or performance load. Furthermore, none of the articles contained a computer model sharing statement, as all studies failed to provide access to simulation code or a sharing statement for model code.

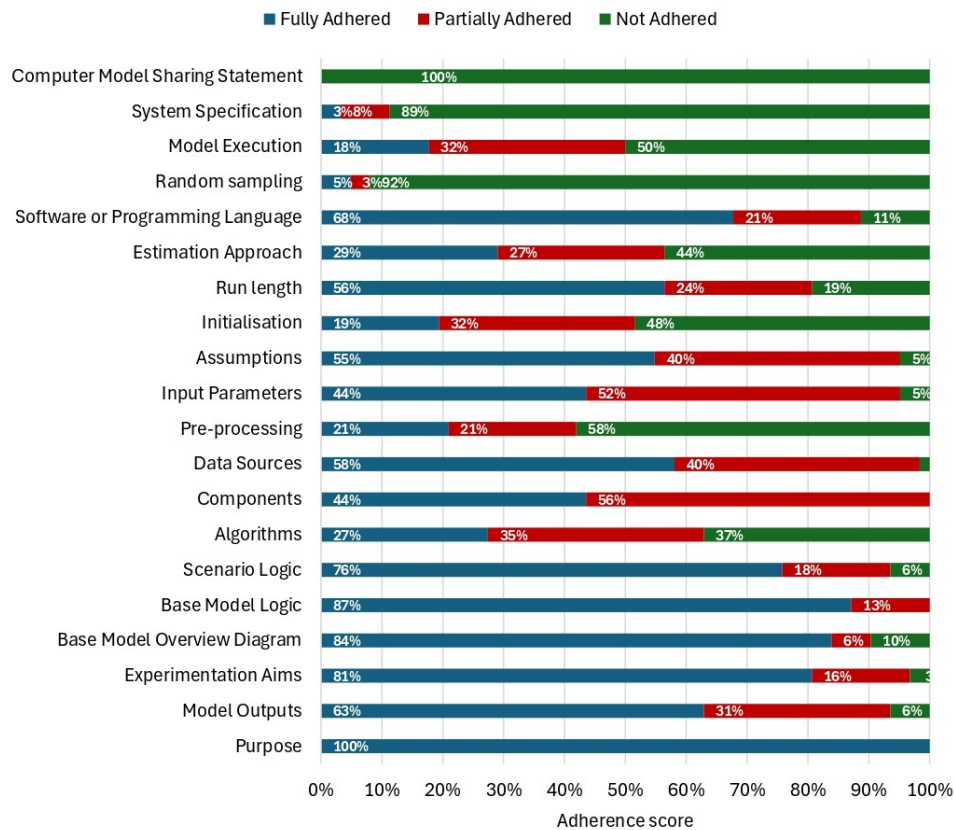


Figure 6: Adherence to STRESS guideline checklist items

4.4 Adherence to the STRESS Guidelines Items Across Simulation Paradigm

Figure 7 shows the adherence scores to the STRESS guidelines across three simulation paradigms: DES, ABS, and SD. The results indicate that both ABS and SD studies have a higher adherence score of 62%, whereas DES studies had an adherence score of 58%.

The results presented in Figure 8 illustrate how well different simulation paradigms adhere to the STRESS guidelines criteria for transparency and reproducibility in simulation studies. Overall, the objective and logic section of the STRESS guideline was largely adhered to with adherence scores above 70% across various simulation paradigms. However, the reporting of the algorithm item varied; DES and ABS studies reported it moderately, with adherence scores of 45% and 58%, respectively. In contrast, SD studies discussed the algorithm item less frequently, resulting in a low adherence score of 33%

In the data and experimentation section, there were slight variations in the adherence level across the simulation paradigm. The result revealed that adherence score across the simulation paradigm ranged from moderate to high for items such as data sources, input parameters, assumptions, and run length. In contrast, pre-processing and estimation approaches reported adherence scores below 48% across the simulation paradigms.

The implementation section demonstrates a low adherence to the system specification and random sampling, with a score below 17%; however, studies that used ABS did not provide information on the random sampling used. Also, there was moderate adherence to model execution in ABS studies, whereas adherence in DES and SD studies was remarkably low. Conversely, the software or programming language used was well documented in both DES and ABS studies, but moderately reported in SD studies

In summary, there was no significant trend in the adherence to most of the sections of the STRESS guidelines. However, the implementation section showed some issues, particularly with items such as system specification, model execution, and random sampling, which were poorly reported.

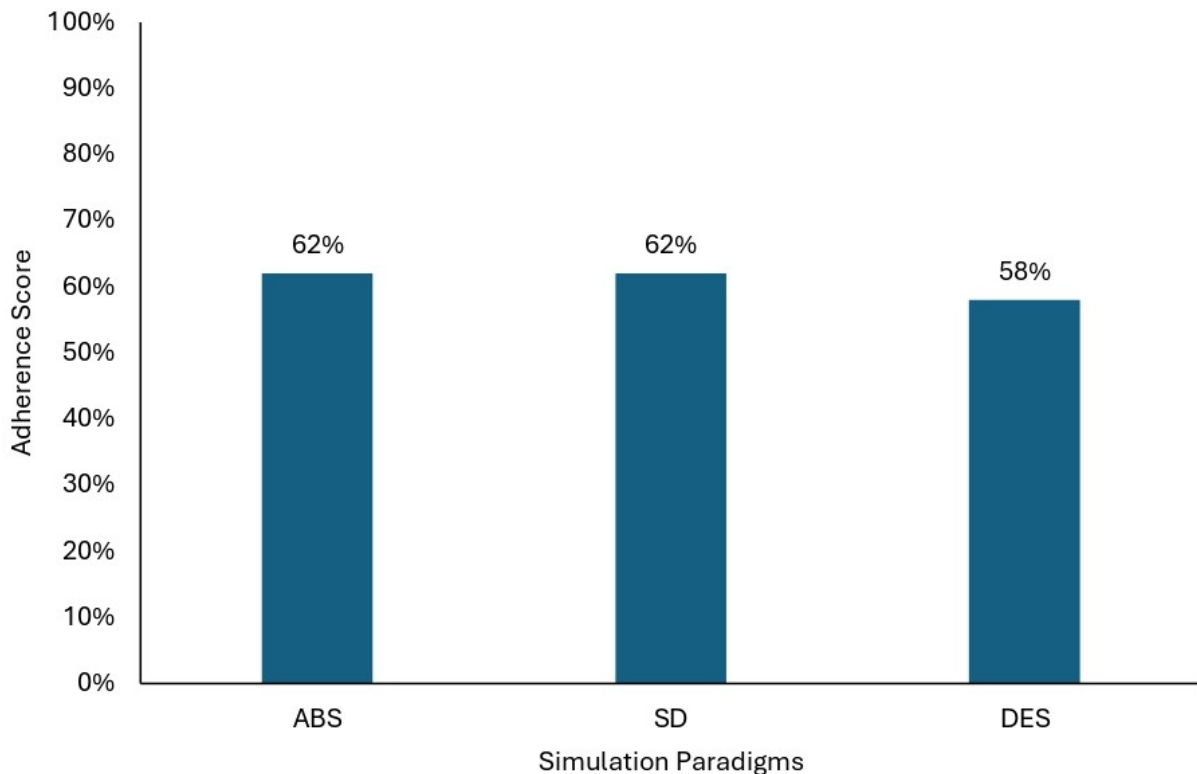


Figure 7: Adherence of studies to STRESS guidelines across simulation paradigms

4.5 Adherence to the STRESS Guidelines Across Journal/Conference Outlets

The result presented in Figure 9 shows the average adherence scores to the STRESS guidelines across the publication outlets. Papers published in SMPT had the highest adherence score at 69%, followed by papers published in JoS at 65%. In contrast, papers from the WSC had a moderate adherence score of 57%, while those published in the SIMULATION journal had the lowest adherence score of 45%.

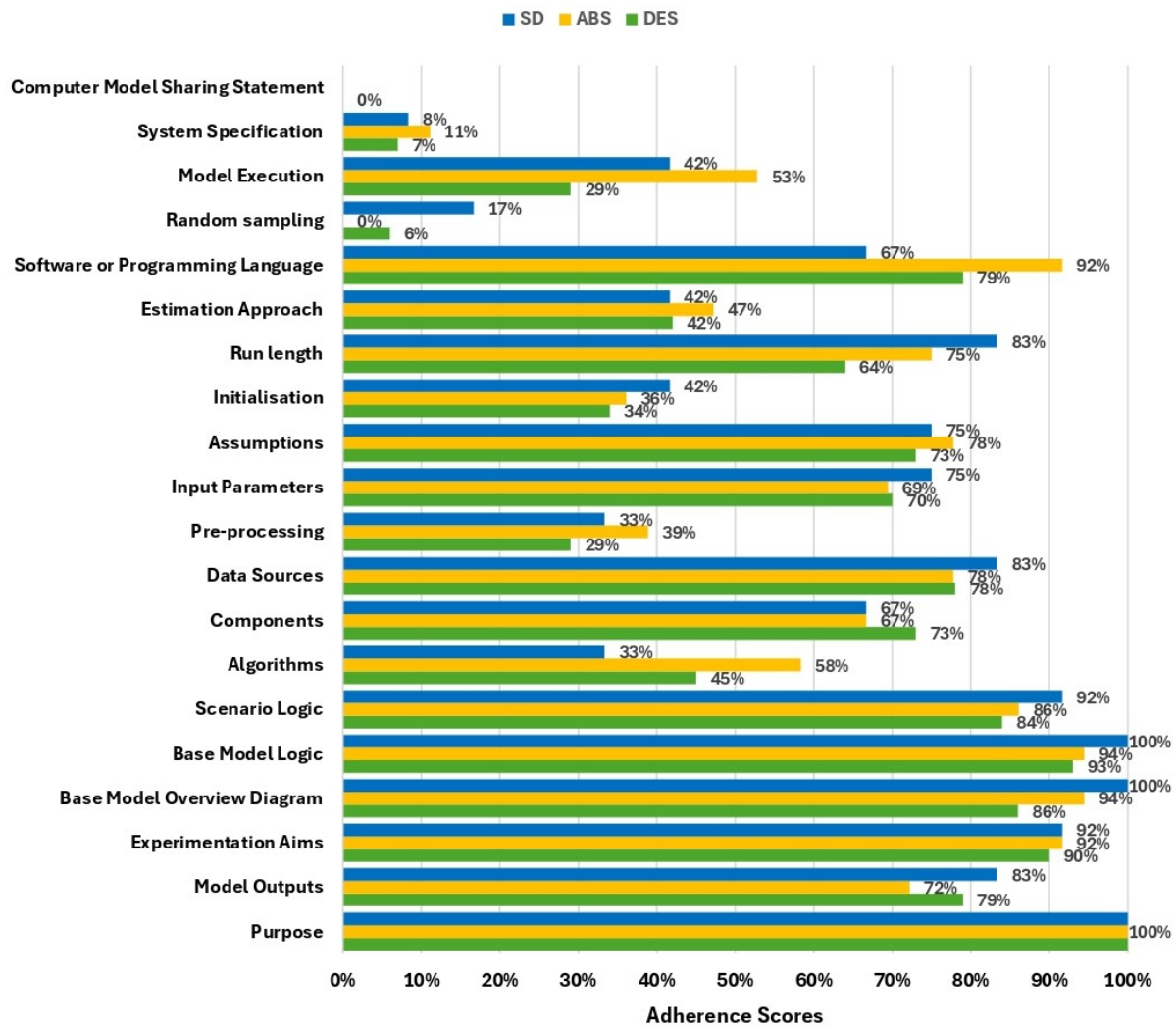


Figure 8: Adherence of studies using different simulation paradigms to STRESS guidelines items

The research revealed that the majority of the publication outlets strongly adhered to the objective and logic section of the STRESS guidelines (Figure 10). Overall, there was high adherence to the reporting of the purpose, experimentation aims and base model logic, with a score over 75%. However, there were variations in adherence to other items within these sections. The journals SMPT, JoS and WSC showed high adherence to reporting basic model overview diagrams and scenario logic, while the SIMULATION journal reported both items moderately. Regarding adherence to the algorithms item, studies published in SMPT showed a high adherence level of 73%. In contrast, JoS and WSC reported moderate adherence at 50%, and SIMULATION had a low adherence score of 10%. In addition, the adherence score for the component items was high (82%) in studies published in SMPT, but it was moderate in other publication outlets.

The adherence level in the data and experimentation section varied across most items. The adherence to the pre-processing, initialisation and estimation approach item used to derive simulation parameters was moderate in SMPT studies, but low in other publication outlets. Additionally, SMPT studies demonstrated a high level of reporting regarding assumptions and run lengths. In contrast, other publication outlets showed moderate reporting of these items, except for the SIMULATION journal, which had less reporting on the run length.

The publication outlets had low reporting in most of the items (Random sampling, model execution, and system specification) with an adherence score less than 30% in the implementation Section. However, there was no report on the random sampling in studies published in SIMULATION journals. In contrast to other items in the implementation section, software or programming language had high adherence in all the publication outlets except for SIMULATION journals, where the adherence was moderate.

In summary, comparing publication outlets, SMPT records the highest adherence scores in most of the guideline items except for random sampling, model execution and system specification. While there was variation in

adherence level for various technical details (data and experimentation) across the publications outlets, the implementation sections were poorly reported.

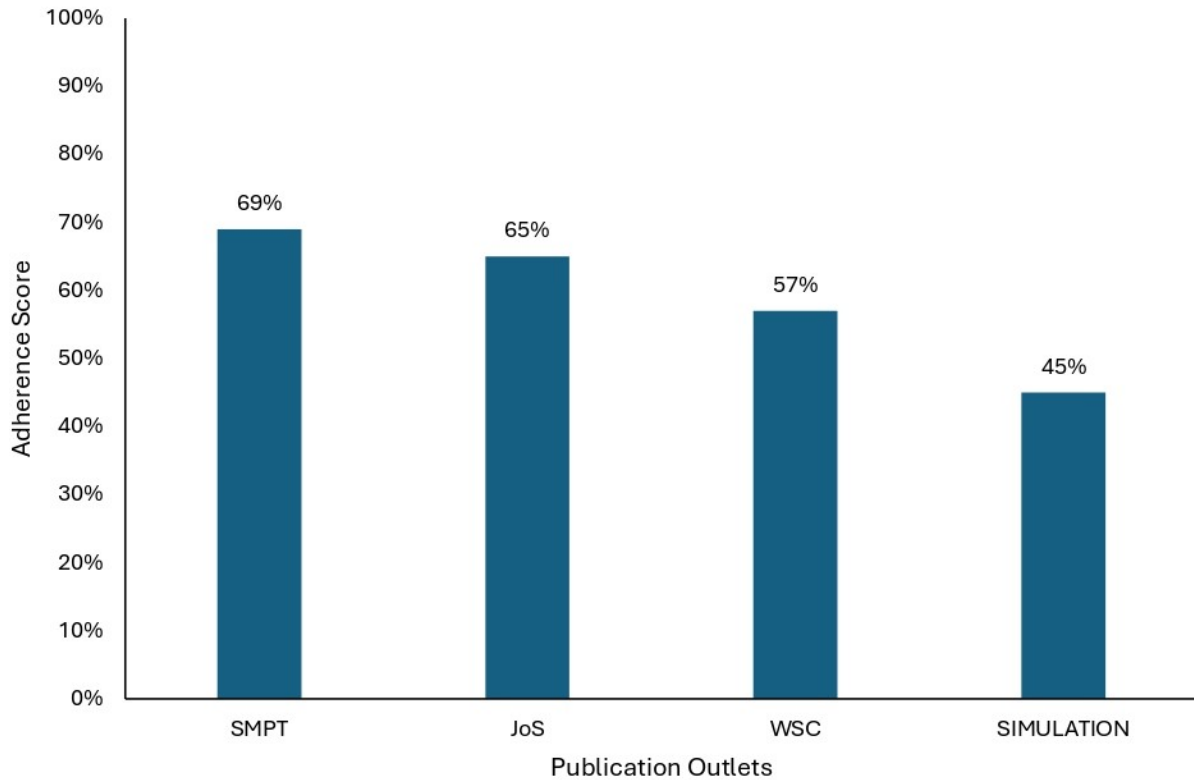


Figure 9: Adherence to STRESS guidelines across publication outlets

4.6 Adherence to the STRESS Guidelines Across Publication Year

The result presented in Figure 11 shows the average adherence scores to the STRESS guidelines across studies published between 2019 and 2024. Studies published in 2019 recorded an adherence score of 63%, followed by a sharp decline to 53% in 2020. In both 2021 and 2022, the adherence score remained the same at 58%. There was a further decline in 2023 to 56%. However, in 2024, studies showed a significant increase, recording the highest adherence score (66%).

The result in Figure 12 demonstrates how simulation research in business processes adhered to the STRESS guidelines over a six-year period. The objectives and logic section was consistently well-reported throughout the years. However, the report on algorithms showed variation; there were moderate reports in 2019, 2023 and 2024, while adherence was notably low from 2020 to 2022.

In the reporting of technical details, which includes Data and Experimentation sections, the adherence level varied for most items over the years. The reporting of data pre-processing, which had a low adherence score from 2019 to 2023, experienced an improvement in 2024. Similarly, the reporting on initialisation showed moderate adherence was seen in studies from 2019 and 2024, while there was low adherence from 2020 to 2023. Adherence to the estimation approach was moderately reported in 2019, 2021 and 2024, but showed low reporting in 2020, 2022 and 2023. Other items, such as data sources, input parameters, assumptions, and run length, exhibited a level of adherence that ranged from moderate to high across the observed years.

On the other hand, there was low reporting on most of the implementation details. For instance, a low adherence level to model execution, random sampling and system specification was observed across the years. Notably, there was an exception of a few that had no reporting, for example, there were specific years with no reporting at all; random sampling was not reported in 2019, 2021 and 2024, while system specification had no reporting in 2021.

Overall, there was no significant trend of improvement in adherence to the STRESS guidelines throughout the years. Although studies in 2024 showed the highest adherence score, this does not necessarily indicate an improvement over time, as there were no consistent increases in adherence from 2020 to 2023.

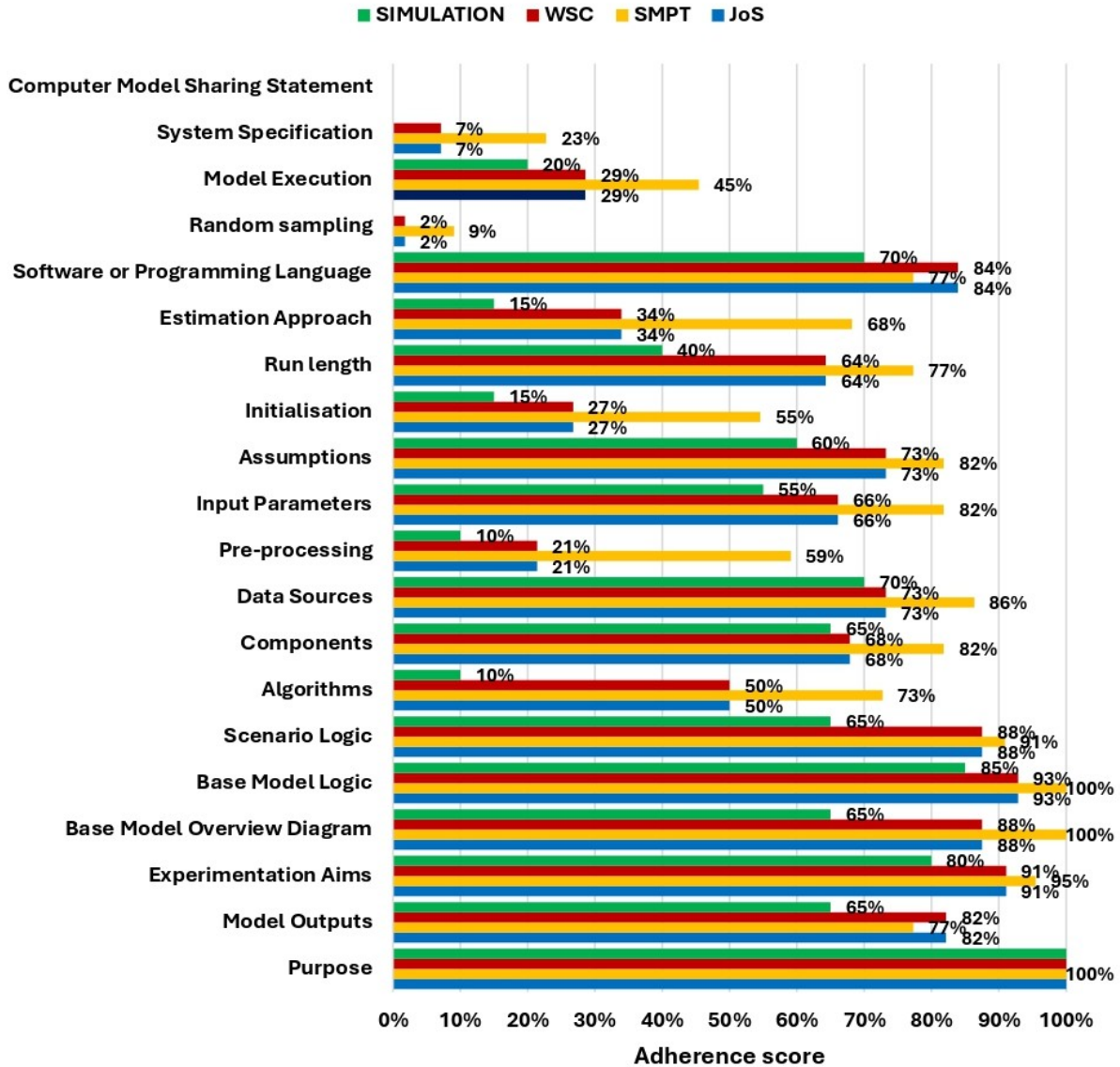


Figure 10: Adherence of different journal/conference outlets to STRESS guidelines checklist

5 Discussion

This study aimed to assess reporting transparency and reproducibility in simulation research by determining how well business process simulation (BPS) case studies follow the STRESS guidelines, which were introduced by Monks et al. (2018). Both progress and limitations in simulation study reporting are revealed by the examination of 62 case studies from a number of prestigious simulation journals and conference proceeding.

The STRESS guidelines show encouraging findings as the results indicate that some guideline items, especially those in the objectives and logic sections, are consistently well addressed, critical elements of the implementation section were not well reported, which posed significant barriers to transparency and reproducibility of simulation models. The studies demonstrated more than 80% compliance with the requirements of the purpose of the model, experimentation aims, base model logic and base Model overview diagrams. The high level of adherence indicates that simulation researchers understand the necessity of clear model intent and structure explanation because these elements are vital for assessing and understanding simulation studies (Monks et al., 2018).

Although the studies show a moderate adherence to the data and experimentation sections of the guidelines, the reporting of the implementation section reveals significant deficiencies, such as random sampling, model execution and system specification. Particularly, less than 20% of studies fully adhere to these details, while in some paradigms, such as ABS, random sampling was not reported at all. This missing detail aligns with gaps identified in other simulation reporting reviews, where implementation specifics are often treated as not important (Rah-

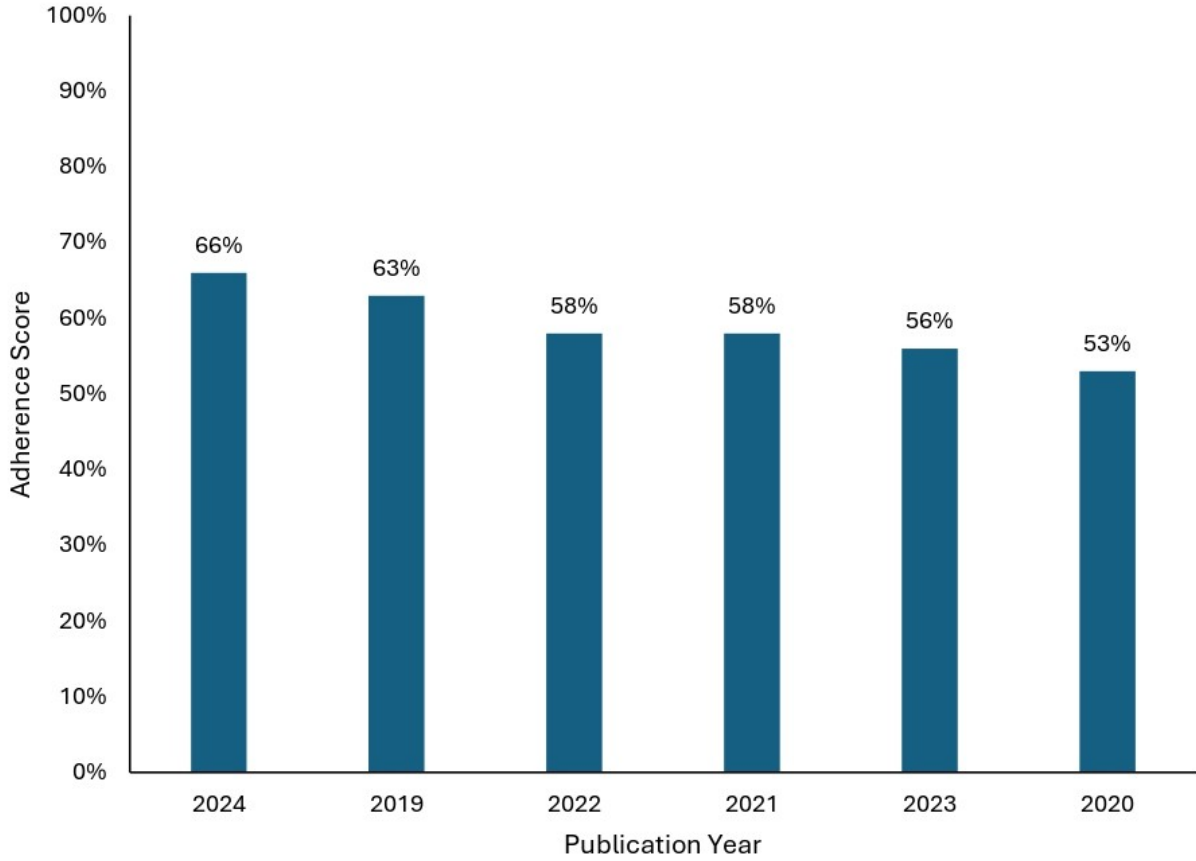


Figure 11: Adherence of studies published across years to STRESS guidelines

mandad & Sterman, 2012). However, STRESS guidelines emphasise that these details are also essential for the reproducibility of studies (Monks et al., 2018). The absence of code-sharing statements in all reviewed studies indicates that open science practices remain neglected in the simulation community. The findings are concerning because code accessibility stands as a primary factor that determines research reproducibility (Antunes & Hill, 2024; Chen et al., 2019).

Differences across simulation paradigms generally show a similar pattern, with SD and ABS showing slightly higher overall adherence scores than DES. The implementation section remains consistently low in adherence across paradigms, although SD studies had weakly reported algorithmic details compared to DES and ABS. This suggests that while methodological approaches within paradigms may influence the emphasis on what is being reported, the issue of adherence to STRESS guidelines is field-wide (Law, 2024).

Analysis of studies by publication outlet suggests that editorial standards and journal culture may influence the adherence levels of STRESS guidelines. Studies published in SMPT and JoS scored the highest overall, especially for data and experimentation reporting, while those in SIMULATION consistently scored lower. This variation suggests that the potential impact of editorial policy could influence authors' reporting, supporting the idea that stronger adherence may be achieved through clearer journal requirements.

In examining the trends across publication years, no consistent improvement was observed in the adherence of studies to STRESS guidelines. Despite 2024 recording the highest average adherence score, the previous years show a series of fluctuations rather than consistent progress. Also, the persistent low reporting of implementation details suggests that the adoption of these guidelines has not yet been translated over the years to ensure reproducibility (Kotiadis et al., 2014).

This study's findings have important implications for the simulation modelling community. First, there is a need for greater emphasis on the implementation section of the STRESS guidelines, as the lack of adherence to this section poses a fundamental constraint to reproducibility (Robinson et al., 2004). With the omission of information on random sampling, software specification and model execution, it becomes difficult to verify if the outcomes are reproducible under the same conditions (Laine et al., 2007; Law, 2024). Second, the variation across journals and paradigms suggests that improvements will require minimum reporting standards to be set in journals and confer-

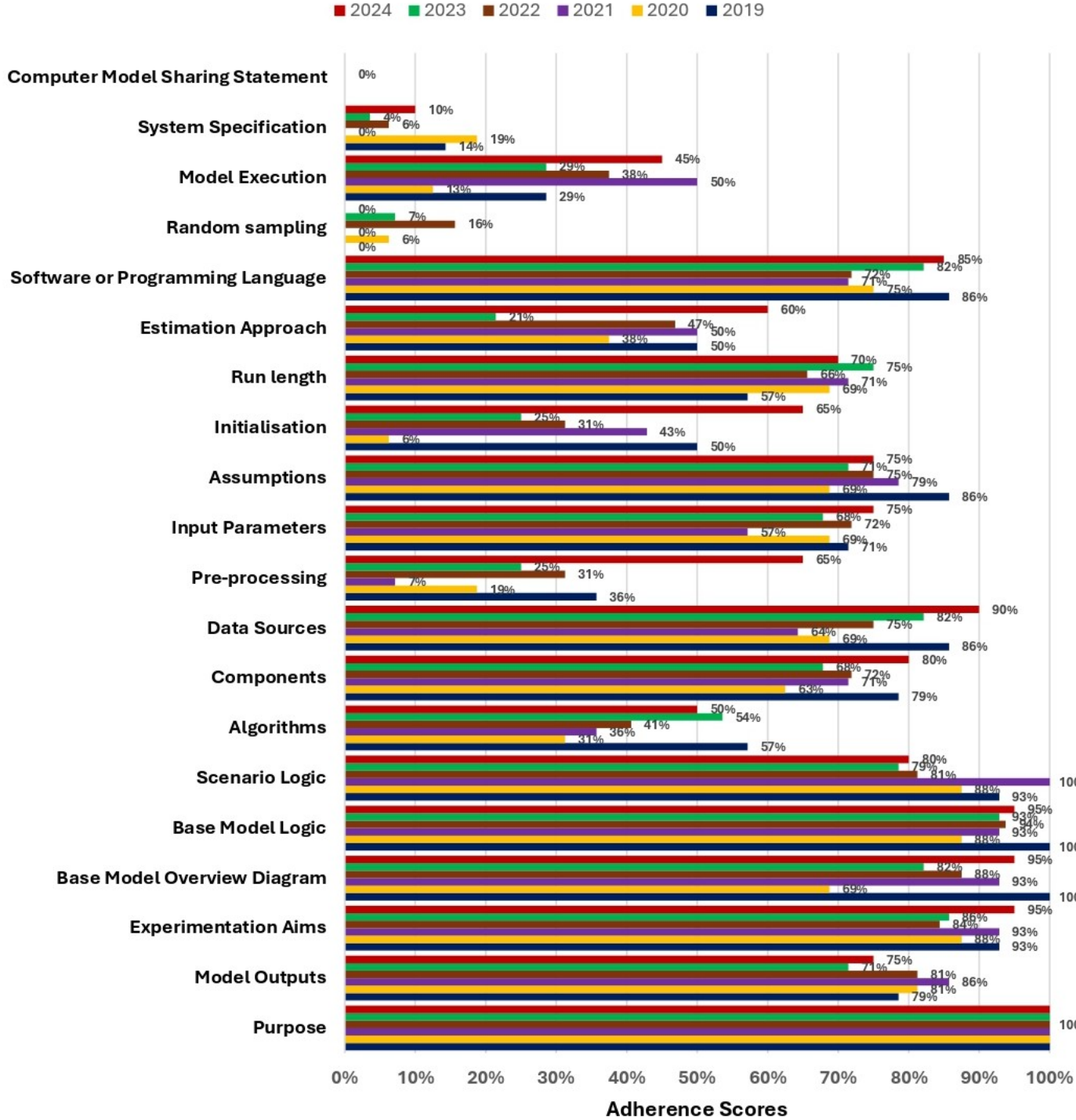


Figure 12: Adherence of studies published across years to STRESS guidelines checklist items

ences, and it could potentially be a requirement to also include STRESS checklists as part of submission, similar to initiatives in the medical and psychological research domains (Feinberg & Rubright, 2016; Williams et al., 2024). Finally, the absence of model-sharing statements creates a major obstacle for achieving open science. The practice of sharing model code, data, and execution environments faces challenges, but becomes more achievable because of control systems versions and repositories. The practice of model sharing remains absent, which prevents simulation research from achieving both verifiability and scalability (Antunes & Hill, 2024; Chen et al., 2019). By making these issues visible, this study will help researchers to improve on making their research accessible to all, which is a way of promoting open science.

This study has some limitations. First, the analysis limited its attention to selected journals and a conference,

limiting the scope of the analysis and may not be fully representative of the wider BPS literature. Second, the scoring system was limited to a ternary system (fully adhered, partially adhered, not adhered), which may overly simplify the complexities of reporting quality. Future research may use a more precise metric to highlight the influences and characteristics of reporting quality. Third, the current study evaluated reporting adherence to the STRESS guidelines but did not measure how reporting quality is related to the reproducibility of findings. It would be useful for an empirical examination of this relationship to be the next step. Finally, the adherence of the case study was assessed by only one person, which could have an impact compared to when assessed by two or more persons.

6 Conclusion

This study evaluated how business process simulation (BPS) case studies published from 2019 to 2024 adhered to the STRESS guidelines outlined by Monks et al. (2018). The researchers introduced the STRESS guidelines to help enhance the transparency, quality, and reproducibility of research based on simulation across simulation paradigms, publication outlets, and years.

The results found that while most of the case study papers strongly adhered to the objectives and logic sections of the simulation reporting by clearly describing their purpose, experimentation aims, and, base model logic, significant weaknesses can be seen in the implementation section especially in the reporting of random sampling methods, system specification, and model execution details, essential for transparency and reproducibility.

Across simulation paradigms, publication outlets, and years, similar patterns occur. While the objective and logic section was well documented, technical implementation details were often underreported, and code-sharing statements were missing. The varying level of adherence among publication outlets suggests that editorial policies can play a major role in influencing reporting adherence. In addition, the lack of consistent improvement over the years highlights the need for a better approach to adopt the STRESS guidelines to ensure a cultural shift toward openness in the simulation community.

There are some avenues for future research that complement this study's findings. First, future research should examine the barriers to STRESS application, with an emphasis on why some important reproducibility measures, such as access to code and random sampling and running model execution, are almost always underreported. Second, researchers could attempt to replicate published models that partially adhere to STRESS guidelines, to quantify how missing technical details (e.g random sampling method, software specifications) affect reproducibility.

References

- Antunes, B., & Hill, D. R. (2024). Reproducibility, replicability and repeatability: A survey of reproducible research with a focus on high performance computing. *Computer Science Review*, 53, 100655.
- Attar, A., Jin, Y., Luis, M., Zhong, S., & Sucala, V. I. (2023). Simulation-based analyses and improvements of the smart line management system in canned beverage industry: A case study in europe. *2023 Winter Simulation Conference (WSC)*, 2124–2135.
- Blinov, M. L., Gennari, J. H., Karr, J. R., Moraru, I. I., Nickerson, D. P., & Sauro, H. M. (2021). Practical resources for enhancing the reproducibility of mechanistic modeling in systems biology. *Current Opinion in Systems Biology*, 27, 100350.
- Boomsma, A. (2013). Reporting monte carlo studies in structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 20(3), 518–540.
- Burton, A., Altman, D. G., Royston, P., & Holder, R. L. (2006). The design of simulation studies in medical statistics. *Statistics in Medicine*, 25(24), 4279–4292.
- Chen, X., Dallmeier-Tiessen, S., Dasler, R., Feger, S., Fokianos, P., Gonzalez, J. B., Hirvonsalo, H., Kousidis, D., Lavasa, A., Mele, S., et al. (2019). Open is not enough. *Nature Physics*, 15(2), 113–119.
- Dehghani, M., Mofatian, N., Rezaei-Hachesu, P., & Samad-Soltani, T. (2017). A step-by-step framework on discrete events simulation in emergency department; a systematic review. *Bulletin of Emergency & Trauma*, 5(2), 79.
- Diaz, M. F. L., Ehm, H., & Ismail, A. (2022). Simulated-based analysis of recovery actions under vendor-managed inventory amid black swan disruptions in the semiconductor industry: A case study from infineon technologies ag. *2022 Winter Simulation Conference (WSC)*, 3513–3524.
- Donkin, E., Dennis, P., Ustalakov, A., Warren, J., & Clare, A. (2017). Replicating complex agent based models, a formidable task. *Environmental Modelling & Software*, 92, 142–151.
- Dumas, M., Rosa, L. M., Mendling, J., & Reijers, A. H. (2018). *Fundamentals of business process management*. Springer.
- Ebrahim, R. A., Singh, S., Li, Y., & Ji, W. (2022). Discrete event simulation for port berth maintenance planning. *2022 Winter Simulation Conference (WSC)*, 2386–2396.
- Fabri, M., Ramalhinho, H., Oliver, M., & Muñoz, J. C. (2022). Internal logistics flow simulation: A case study in automotive industry. *Journal of Simulation*, 16(2), 204–216.

- Fava, G., Giovannelli, T., Messedaglia, M., & Roma, M. (2022). Effect of different patient peak arrivals on an emergency department via discrete event simulation: A case study. *Simulation*, 98(3), 161–181.
- Feinberg, R. A., & Rubright, J. D. (2016). Conducting simulation studies in psychometrics. *Educational Measurement: Issues and Practice*, 35(2), 36–49.
- Fitzpatrick, B. G. (2019). Issues in reproducible simulation research. *Bulletin of Mathematical Biology*, 81, 1–6.
- Garcia-Vicuña, D., Mallor, F., & Esparza, L. (2020). Planning ward and intensive care unit beds for covid-19 patients using a discrete event simulation model. *2020 Winter Simulation Conference (WSC)*, 759–770.
- Giabbanelli, P. J., Tison, B., & Keith, J. (2021). The application of modeling and simulation to public health: Assessing the quality of agent-based models for obesity. *Simulation Modelling Practice and Theory*, 108, 102268.
- Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G., et al. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, 198(1-2), 115–126.
- Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The odd protocol: A review and first update. *Ecological Modelling*, 221(23), 2760–2768.
- Günel, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation*, 4(1), 42–51.
- Hallgren, K. A. (2013). Conducting simulation studies in the r programming environment. *Tutorials in Quantitative Methods for Psychology*, 9(2), 43.
- Jen, H.-C., Huff, B. L., LeBoulluec, A. K., Nasirian, B., Bum Kim, S., Rosenberger, J. M., & Chen, V. C. (2022). A discrete-event simulation tool for airport deicing activities: Dallas-fort worth international airport. *Simulation*, 98(12), 1097–1114.
- Kotiadis, K., Tako, A. A., & Vasilakis, C. (2014). A participative and facilitative conceptual modelling framework for discrete event simulation studies in healthcare. *Journal of the Operational Research Society*, 65(2), 197–213.
- Laine, C., Goodman, S. N., Griswold, M. E., & Sox, H. C. (2007). Reproducible research: Moving toward research the public can really trust. *Annals of Internal Medicine*, 146(6), 450–453.
- Lane, D. C. (2000). Should system dynamics be described as a ‘hard’ or ‘deterministic’ systems approach? *Systems Research and Behavioral Science: the official journal of the international federation for systems research*, 17(1), 3–22.

- Lang, L., Chwif, L., & Pereira, W. (2022). Decision-making impacts of originating picking waves process for a distribution center using discrete-event simulation. *2022 Winter Simulation Conference (WSC)*, 1509–1520.
- Law, A. M. (2024). *Simulation modeling and analysis* (Sixth). McGraw-Hill.
- Melao, N., & Pidd, M. (2003). Use of business process simulation: A survey of practitioners. *Journal of The Operational Research Society*, 54, 2–10.
- Monks, T., Currie, C. S., Onggo, B. S., Robinson, S., Kunc, M., & Taylor, S. J. (2018). Strengthening the reporting of empirical simulation studies: Introducing the stress guidelines. *Journal of Simulation*, 13(1), 55–67.
- Mousavi, B. A., Azzouz, R., Heavey, C., & Ehm, H. (2019). Simulation-based analysis of the nervousness within semiconductors supply chain planning: Insight from a case study. *2019 Winter Simulation Conference (WSC)*, 2396–2407.
- Navarro, J., Deruyver, A., & Parrend, P. (2018). A systematic survey on multi-step attack detection. *Computers & Security*, 76, 214–249.
- Özkan, E. D., Koçer, U. U., Nas, S., İşlek, Ö., Tüzgen, E., & Doğan, A. (2023). A simulation model for evaluating the cargo transfer alternatives in liquid cargo terminals. *Simulation*, 99(1), 23–39.
- Paxton, P., Curran, P. J., Bollen, K. A., Kirby, J., & Chen, F. (2001). Monte carlo experiments: Design and implementation. *Structural Equation Modeling*, 8(2), 287–312.
- Rahmandad, H., & Sterman, J. (2012). Reporting guidelines for simulation-based research in social sciences. *System Dynamics Review*, 28.
- Ring, L., Höfer, S., Heuston, F., Harris, D., & O’Boyle, C. A. (2005). Response shift masks the treatment impact on patient reported outcomes (pros): The example of individual quality of life in edentulous patients. *Health and Quality of Life Outcomes*, 3, 1–8.
- Robinson, S. (2014). *Simulation: The practice of model development and use*. Bloomsbury Publishing.
- Robinson, S., Nance, R. E., Paul, R. J., Pidd, M., & Taylor, S. J. (2004). Simulation model reuse: Definitions, benefits and obstacles. *Simulation Modelling Practice and Theory*, 12(7-8), 479–494.
- Sawatzky, R., Sajobi, T. T., Brahmabhatt, R., Chan, E. K., Lix, L. M., & Zumbo, B. D. (2017). Longitudinal change in response processes: A response shift perspective. *Understanding and Investigating Response Processes in Validation Research*, 251–276.
- Serrano-Hernandez, A., Faulin, J., de la Torre, R., & Cadarso, L. (2020). Agent-based simulation improves e-grocery deliveries using horizontal cooperation. *2020 Winter Simulation Conference (WSC)*, 1242–1253.

- Skrondal, A. (2000). Design and analysis of monte carlo experiments: Attacking the conventional wisdom. *Multivariate Behavioral Research*, 35(2), 137–167.
- Sung, Y.-W., Chu, J. C., Chang, Y.-J., Yeh, J.-C., & Chou, Y.-H. (2022). Optimizing mix of heterogeneous buses and chargers in electric bus scheduling problems. *Simulation Modelling Practice and Theory*, 119, 102584.
- Taylor, S. J., Anagnostou, A., Fabiyi, A., Currie, C., Monks, T., Barbera, R., & Becker, B. (2017). Open science: Approaches and benefits for modeling & simulation. *2017 Winter Simulation Conference (WSC)*, 535–549.
- Uhrmacher, A. M., Brailsford, S., Liu, J., Rabe, M., & Tolk, A. (2016). Panel—reproducible research in discrete event simulation—a must or rather a maybe? *2016 Winter Simulation Conference (WSC)*, 1301–1315.
- Waltemath, D., Adams, R., Beard, D. A., Bergmann, F. T., Bhalla, U. S., Britten, R., Chelliah, V., Cooling, M. T., Cooper, J., Crampin, E. J., et al. (2011). Minimum information about a simulation experiment (*MIASE*). *PLoS Computational Biology*, 7(4), e1001122.
- Williams, C., Yang, Y., Lagisz, M., Morrison, K., Ricolfi, L., Warton, D. I., & Nakagawa, S. (2024). Transparent reporting items for simulation studies evaluating statistical methods: Foundations for reproducibility and reliability. *Methods in Ecology and Evolution*, 15(11), 1926–1939.
- Yilmaz, L., Taylor, S., Fujimoto, R., & Darema, F. (2014). Panel: The future of research in modeling simulation. *Proceedings of the 2014 Winter Simulation Conference, Ser. WSC'14*, 2797–2811.
- Zhang, J., & Robinson, D. T. (2021). Replication of an agent-based model using the replication standard. *Environmental Modelling & Software*, 139, 105016.

Strengthening the Reporting of Empirical Simulation Studies (STRESS)

by Monks et al. (2018)

A APPENDIX A: STRESS-DES by Monks et al. (2018)

Section/Subsection	Item	Criteria	
Objectives			
Purpose of the model	1.1	Explain the background and objectives for the model.	
Model Outputs	1.2	Define all quantitative performance measures that are reported, using equations where necessary. Specify how and when they are calculated during the model run along with how any measures of error such as confidence intervals are calculated.	
Experimentation Aims	1.3	<ul style="list-style-type: none">• If the model has been used for experimentation, state the objectives that it was used to investigate.• Scenario based analysis – Provide a name and description for each scenario, providing a rationale for the choice of scenarios and ensure that item 2.3 (below) is completed.• Design of experiments – Provide details of the overall design of the experiments with reference to performance measures and their parameters (provide further details in <i>data</i> below).• Simulation Optimisation – (if appropriate) Provide full details of what is to be optimised, the parameters that were included and the algorithm(s) that was be used. Where possible provide a citation of the algorithm(s).	
Logic			
Base model overview diagram	2.1	Describe the base model using appropriate diagrams and description. This could include one or more process flow, activity cycle or equivalent diagrams sufficient to describe the model to readers. Avoid complicated diagrams in the main text. The goal is to describe the breadth and depth of the model with respect to the system being studied.	
Base model logic	2.2	Give details of the base model logic. Give additional model logic details sufficient to communicate to the reader how the model works.	
Scenario logic	2.3	Give details of the logical difference between the base case model and scenarios (if any). This could be incorporated as text or where differences are substantial could be incorporated in the same manner as 2.2.	
Algorithms	2.4	Provide further detail on any algorithms in the model that (for example) mimic complex or manual processes in the real world (i.e. scheduling of arrivals/appointments/operations/maintenance, operation of a conveyor system, machine breakdowns, etc.). Sufficient detail should be included (or referred to in other published work) for the algorithms to be reproducible. Pseudo-code may be used to describe an algorithm.	
Components	2.5	2.5.1 Entities	Give details of all entities within the simulation including a description of their role in the model and a description of all their attributes.
		2.5.2 Activities	Describe the activities that entities engage in within the model. Provide details of entity routing into and out of the activity.

Section/Subsection	Item	Criteria
		2.5.3 Resources List all the resources included within the model and which activities make use of them.
		2.5.4 Queues Give details of the assumed queuing discipline used in the model (e.g. First in First Out, Last in First Out, prioritisation, etc.). Where one or more queues have a different discipline from the rest, provide a list of queues, indicating the queuing discipline used for each. If reneging, balking or jockeying occur, etc., provide details of the rules. Detail any delays or capacity constraints on the queues.
		2.5.5 Entry/Exit Points Give details of the model boundaries i.e. all arrival and exit points of entities. Detail the arrival mechanism (e.g. 'thinning' to mimic a non-homogenous Poisson process or balking)
Data		
Data sources	3.1	List and detail all data sources. Sources may include: <ul style="list-style-type: none"> • Interviews with stakeholders, • Samples of routinely collected data, • Prospectively collected samples for the purpose of the simulation study, • Public domain data published in either academic or organisational literature. Provide, where possible, the link and DOI to the data or reference to published literature. All data source descriptions should include details of the sample size, sample date ranges and use within the study.
Pre-processing	3.2	Provide details of any data manipulation that has taken place before its use in the simulation, e.g. interpolation to account for missing data or the removal of outliers.
Input parameters	3.3	List all input variables in the model. Provide a description of their use and include parameter values. For stochastic inputs provide details of any continuous, discrete or empirical distributions used along with all associated parameters. Give details of all time dependent parameters and correlation. Clearly state: <ul style="list-style-type: none"> • Base case data • Data use in experimentation, where different from the base case. • Where optimisation or design of experiments has been used, state the range of values that parameters can take. Where theoretical distributions are used, state how these were selected and prioritised above other candidate distributions.
Assumptions	3.4	Where data or knowledge of the real system is unavailable what assumptions are included in the model? This might include parameter values, distributions or routing logic within the model.
Experimentation		
Initialisation	4.1	Report if the system modelled is terminating or non-terminating. State if a warm-up period has been used, its length and the analysis method used to select it. For terminating systems state the stopping condition. State what if any initial model conditions have been included, e.g., pre-loaded queues and activities. Report whether initialisation of these variables is deterministic or stochastic.
Run length	4.2	Detail the run length of the simulation model and time units.

Section/Subsection	Item	Criteria
Estimation approach	4.3	State the method used to account for the stochasticity: For example, two common methods are multiple replications or batch means. Where multiple replications have been used, state the number of replications and for batch means, indicate the batch length and whether the batch means procedure is standard, spaced or overlapping. For both procedures provide a justification for the methods used and the number of replications/size of batches.
Implementation		
Software or programming language	5.1	<p>State the operating system and version and build number.</p> <p>State the name, version and build number of commercial or open source DES software that the model is implemented in.</p> <p>State the name and version of general-purpose programming languages used (e.g. Python 3.5).</p> <p>Where frameworks and libraries have been used provide all details including version numbers.</p>
Random sampling	5.2	<p>State the algorithm used to generate random samples in the software/programming language used e.g. Mersenne Twister.</p> <p>If common random numbers are used, state how seeds (or random number streams) are distributed among sampling processes.</p>
Model execution	5.3	<p>State the event processing mechanism used e.g. three phase, event, activity, process interaction.</p> <p><i>Note that in some commercial software the event processing mechanism may not be published. In these cases authors should adhere to item 5.1 software recommendations.</i></p> <p>State all priority rules included if entities/activities compete for resources.</p> <p>If the model is parallel, distributed and/or use grid or cloud computing, etc., state and preferably reference the technology used. For parallel and distributed simulations the time management algorithms used. If the HLA is used then state the version of the standard, which run-time infrastructure (and version), and any supporting documents (FOMs, etc.)</p>
System Specification	5.4	State the model run time and specification of hardware used. This is particularly important for large scale models that require substantial computing power. For parallel, distributed and/or use grid or cloud computing, etc. state the details of all systems used in the implementation (processors, network, etc.)
Code Access		
Computer Model Sharing Statement	6.1	Describe how someone could obtain the model described in the paper, the simulation software and any other associated software (or hardware) needed to reproduce the results. Provide, where possible, the link and DOIs to these.

B APPENDIX B: STRESS-ABS by Monks et al. (2018)

Section/Subsection	Item	Criteria
Objectives		
Purpose of the model	1.1	Explain the background and rationale for the model.

Section/Subsection	Item	Criteria
Model Outputs	1.2	<p>State the qualitative or quantitative system level outputs that emerge from agent interactions within the ABS.</p> <p>Define all quantitative performance measures that are reported, using equations where necessary. Specify how and when they are calculated during the model run along with how any measures of error such as confidence intervals are calculated</p>
Experimentation Aims	1.3	<p>If the model has been used for experimentation, state the research questions that it was used to answer.</p> <p>Theory driven analysis. – Provide details and reference the theories that are tested within the model.</p> <p>Scenario based analysis – Provide a name and description for each scenario, including a rationale for the choice of scenarios and ensure that item 2.3 (below) is completed.</p> <p>Design of experiments – Provide details of the overall design of the experiments with reference to performance measures and their parameters (provide further details in <i>data</i> below).</p> <p>Simulation Optimisation – (if appropriate) Provide full details of what is to be optimised, the parameters that were included and the algorithm(s) that was be used. Where possible provide a citation of the algorithm(s).</p>
Logic		
Base model overview diagram	2.1	Provide one or more of: state chart, process flow or equivalent diagrams to describe the basic logic of the base model to readers. Avoid complicated diagrams in the main text.
Base model logic	2.2	Give details of the base model logic. This could be text to explain the overview diagram along with extra details including ABS product and process patterns. Include details of all intermediate calculations.
Scenario logic	2.3	Give details of any difference in the model logic between the base case model and scenarios. This could be incorporated as text or, where differences are substantial, could be incorporated in the same manner as 2.1.
Algorithms	2.4	Provide further detail on any algorithms in the model that (for example) mimic complex or manual processes in the real world (i.e. scheduling of arrivals/appointments/operations/maintenance, operation of a conveyor system, machine breakdowns, etc.). Sufficient detail should be included (or referred to in other published work) for the algorithms to be reproducible. Pseudo-code may be used to describe an algorithm.
Components	2.5	<div>2.5.1. Environment</div> <p>Describe the environment agents interact within, indicating its structure, and how it is generated. For example, are agents bound within a homogeneous grid, or do they have continuous movement through a detailed landscape incorporating geographic or environmental information?</p>

Section/Subsection	Item	Criteria
		<p>2.5.2. Agents</p> <p>List all agents and agent groups within the simulation. Include a description of their role in the model, their possible states, state transitions, and all their attributes.</p> <p>Describe all decision-making rules that agents follow in either algorithmic or equation form. Where relevant authors should report:</p> <p>The data that agents access (I.e. internal attributes or external information from the environment) and how it is used.</p> <p>The objectives agents seek to achieve.</p> <p>The algorithms, optimisations, heuristics and rules that agents use to achieve objectives.</p> <p>How agents work together within a group along with any rules for changes in group membership.</p> <p>Predictions of future events and adaptive action.</p>
		<p>2.5.3. Interaction Topology</p> <p>Describe how agents and agent groupings are connected with each other in the model define:</p> <p>with whom agents can interact,</p> <p>how recipients of interactions are selected</p> <p>what frequency interaction occurs.</p> <p>How agents handle and assign priorities to concurrent events</p> <p>It is recommended that interactions are described using a combination of equations pseudo-code and logic diagrams.</p> <p>Report how interactions are affected by agent states and the environment state</p>
		<p>2.5.4 Entry / Exit</p> <p>Where relevant, define how agents are created and destroyed in the model.</p>
Data		
Data sources	3.1	<p>List and detail all data sources. Sources may include:</p> <ul style="list-style-type: none"> • Interviews with stakeholders • samples of routinely collected data, • prospectively collected samples for the purpose of the simulation study, public domain data published in either academic or organisational literature. Provide, where possible, the link and DOI to the data or reference to published literature. <p>All data source descriptions should include details of the sample size, date ranges and use within the study.</p>
Pre-processing	3.2	<p>Provide details of any data manipulation or filtering that has taken place before its use in the simulation, e.g. interpolation to account for missing data, removal of outliers or filtering of large scale data.</p>

Section/Subsection	Item	Criteria
Input parameters	3.3	<p>List all input parameters in the model, providing a description of each parameter and the values used. For stochastic inputs provide details of any continuous, discrete or empirical distributions used along with all associated parameters. Where applicable define the time/spatial dependence of parameters and any correlation structure.</p> <p>Clearly state:</p> <ul style="list-style-type: none"> • Base case inputs • Inputs used in experimentation, where different from the base case. • Where optimisation or design of experiments has been used, state the range of values that parameters can take. <p>Where theoretical distributions are used, state how, , these were selected and prioritised above other candidate distributions.</p>
Assumptions	3.4	Where data or knowledge of the real system is unavailable, state and justify the assumptions used to set input parameter values and distributions; agent interactions or behaviour; or model logic.
Experimentation		
Initialisation	4.1	<p>State if a warm-up period has been used, its length and the analysis method used to select it.</p> <p>State what if any initial agent and environmental conditions have been included. For example, the initial agent population size, agent states and attributes, initial agent network structure(s), and resources within the environment. Report whether initialisation of these variables is deterministic or stochastic.</p>
Run length	4.2	Detail the run length of the simulation model and time units.
Estimation approach	4.3	State if the model is deterministic or stochastic. If the model is stochastic, state the number of replications that have been used. If an alternative estimation method has been used (e.g. batch means), provide full details.
Implementation		
Software or programming language	5.1	<p>State the operating system and version and build number.</p> <p>State the name, version and build number of commercial or open source ABS software that the model is implemented in.</p> <p>State the name and version of general-purpose programming languages used (e.g. Python 3.5.2). Where packages, frameworks and libraries have been used provide all detailed including version numbers.</p>
Random sampling	5.2	State the algorithm or package used to generate random samples within the software/programming language used e.g. Mersenne Twister or Java.Random version x.y
Model execution	5.3	<p>If the ABS model has a time component, describe how time is modelled (e.g. fixed time steps or discrete-event). State the order of variable updating within the model. In time-stepped execution state how concurrent events are resolved.</p> <p>If the model is parallel, distributed and/or use grid or cloud computing, etc., state and preferably reference the technology used. For parallel and distributed simulations the time management algorithms used. If the HLA is used then state the version of the standard, which run-time infrastructure (and version), and any supporting documents (FOMs, etc.)</p>
System Specification	5.4	State the model run time and specification of hardware used. This is particularly important for large scale models that require substantial computing power. For parallel, distributed and/or use grid or cloud computing, etc. state the details of all systems used in the implementation (processors, network, etc.)
Code Access		

Section/Subsection	Item	Criteria
Computer Model Sharing Statement	6.1	Describe how someone could obtain the model described in the paper, the simulation software and any other associated software (or hardware) needed to reproduce the results. Provide, where possible, the link and DOIs to these.

C APPENDIX C: STRESS-SD by Monks et al. (2018)

Section/Subsection	Item	Criteria				
Objectives						
Purpose of the model	1.1	Explain the background and rationale for the model.				
Model Outputs	1.2	Describe all outcome variables that are reported. Include details on how they are calculated during the model run. These might be as simple as detailing which specific stocks/levels are of key interest or may involve detailing equations.				
Experimentation Aims	1.3	<p>If the model has been used for policy analysis (user-defined experiments) and policy formulation (multiple experiments to obtain best policy), state the research questions that it was used to answer.</p> <p>Policy based analysis – Provide a name and description of each policy tested, providing a rationale for the choice of policies and parameters employed. Ensure that item 2.3 (below) is completed.</p> <p>Design of experiments – Provide details of the design and the parameters that will be used. This for example, may be to perform a sensitivity analysis.</p> <p>Simulation Optimisation - Provide full details of what is to be optimised and the parameters that will be included and the algorithm that will be used. Where possible provide a citation of the algorithm/calibration method.</p>				
Logic						
Base model overview diagram	2.1	Provide one or more causal loop, stock and flow (a.k.a level and rate) or equivalent diagrams to describe the basic logic of base model to readers. Avoid complicated diagrams in the main text. To aid readers understanding authors should document the key feedback loops that drive system behaviour.				
Base model logic	2.2	Give details of the base model logic in terms of feedback loops. This could be text to explain the overview diagram along with extra details including any use of system archetypes.				
Scenario logic	2.3	Give details of the logical difference between the base case model and policies, scenarios and experiments. This could be incorporated as text, or where differences are substantial could be incorporated in the same manner as 2.1.				
Algorithms	2.4	Provide detail on any algorithms, functions or equations that mimic complex or manual processes in the real world. E.g. scheduling of arrivals/appointments/operations/maintenance. Sufficient detail should be included (or referred to in other published work) for the algorithms to be reproducible. For clarity, it is recommended that algorithms are represented as pseudo-code.				
Components	2.5	<table><tr><td>2.5.1 Stocks/Levels</td><td>Give details of all stocks within the simulation including a description of their role in the model. Provide the stocks units and make sure that all inflows and outflows can easily be identified (note that in a large model a diagram is unlikely to sufficiently clear for other researchers to use. Please consider tables in addition to any diagrams).</td></tr><tr><td>2.5.2 Flows/Rates</td><td>List all flows within the model along with units and equations. Describe the role of flows in the model e.g. if they act a delay.</td></tr></table>	2.5.1 Stocks/Levels	Give details of all stocks within the simulation including a description of their role in the model. Provide the stocks units and make sure that all inflows and outflows can easily be identified (note that in a large model a diagram is unlikely to sufficiently clear for other researchers to use. Please consider tables in addition to any diagrams).	2.5.2 Flows/Rates	List all flows within the model along with units and equations. Describe the role of flows in the model e.g. if they act a delay.
2.5.1 Stocks/Levels	Give details of all stocks within the simulation including a description of their role in the model. Provide the stocks units and make sure that all inflows and outflows can easily be identified (note that in a large model a diagram is unlikely to sufficiently clear for other researchers to use. Please consider tables in addition to any diagrams).					
2.5.2 Flows/Rates	List all flows within the model along with units and equations. Describe the role of flows in the model e.g. if they act a delay.					

Section/Subsection	Item	Criteria
		2.5.3 Constants / Converters / auxiliary variables
		List all variables within the model and detail their equations (if applicable) including units.
		2.5.4 Graphical functions/lookup tables
		List and detail all graphical functions within the model and describe their data sources.
		2.5.5 Sources and Sinks
		Give details of the model boundaries i.e. all infinite sources and sinks within the model.
Data		
Data sources	3.1	<p>List and detail of all data sources. Sources may include:</p> <ul style="list-style-type: none"> • Interviews with stakeholders, • samples of routinely collected data, • prospectively collected samples for the purpose of the simulation study , • Public domain data published in either academic or organisational literature. <p>For published literature include the reference.</p> <p>All data source descriptions should include details of the sample size, date ranges and use within the study.</p>
Pre-processing	3.2	Provide details of any data manipulation that has taken place before its use in the simulation, e.g. interpolation to account for missing data or the removal of outliers.
Input parameters	3.3	<p>List of all input variables in the model, provide a description of its use and include parameter values. For stochastic inputs provide details of any continuous, discrete or empirical distributions used along with all associated parameters. Give details of all time dependent parameters, correlation and any graphical functions.</p> <p>Clearly state:</p> <ul style="list-style-type: none"> • Base case data • Data use in experimentation (where different from the base case). • Where optimisation or design of experiments has been used, state the range of values that parameters can take. <p>Where theoretical distributions are used, state how these were these selected and prioritised above other candidate distributions.</p>
Assumptions	3.4	Where data or knowledge of the real system is unavailable what assumptions are included in the model? This might include parameter values, distributions or flow logic within the model.
Experimentation		
Initialisation	4.1	<p>List all initial values of stocks and auxiliary variables within the model.</p> <p>Provide details of empirical or theoretical distributions used, if initial values are varied over multiple runs of the model (e.g. for calibration or optimisation).</p>
Run length	4.2	Detail the run length of the simulation model and time units
Estimation approach	4.3	<p>If the SD model includes stochastic inputs report if multiple replications or an alternative approach has been used in estimating model outputs.</p> <p>For model calibration or optimisation report the algorithm/search method used and the number replications (runs) of the simulation model.</p>
Implementation		

Section/Subsection	Item	Criteria
Software or programming language	5.1	<p>State the operating system and version and build number.</p> <p>State the name, version and build number of commercial or open source SD software that the model is implemented in (e.g. Vensim, iThink, Insight-Maker). Many modern SD packages provide specialised stocks to act as delays e.g. conveyers, queues and ovens. Provide details all specialised stocks and where they are used in the model.</p> <p>State the name and version of general-purpose programming languages used (e.g. Python 3.5.2). Where packages, frameworks and libraries have been used provide all detailed including version numbers.</p>
Random sampling	5.2	State the algorithm used to generate random samples with in the software/programming language used e.g. Mersenne Twister.
Model execution	5.3	Report the integration method used along with time step settings.
System Specification	5.4	State the model run time and specification of hardware used. This is particularly important for large scale models that require substantial computing power.
Code Access		
Computer Model Sharing Statement	6.1	Describe how someone could obtain the model described in the paper, the simulation software and any other associated software (or hardware) needed to reproduce the results. Provide, where possible, the link and DOIs to these.

D APPENDIX D: Summary of Articles Analysed

S/N	Year	Author	Title	Publication Outlets
1	2022	Fabri, et al. (2022)	Internal logistics flow simulation: A case study in automotive industry	Journal of Simulation
2	2024	Longo, et al. (2024)	A simulation model for addressing supply chain disruptions under a multi-capital sustainability perspective: a case study in the agri-food sector	Journal of Simulation
3	2020	Hassannayebi, et al. (2020)	A hybrid simulation model of passenger emergency evacuation under disruption scenarios: A case study of a large transfer railway station	Journal of Simulation
4	2022	Suryani, et al. (2022)	A simulation model to improve the value of rice supply chain (A case study in East Java – Indonesia)	Journal of Simulation
5	2022	Shahabi, et al. (2022)	An event-driven simulation-optimisation approach to improve the resiliency of operation in a double-track urban rail line	Journal of Simulation
6	2021	Ermolova, et al. (2021)	Agent-based model of the Russian banking system: Calibration for maturity, interest rate spread, credit risk, and capital regulation	Journal of Simulation
7	2023	Terán, et al. (2023).	Modeling and simulating Chinese cross-border e-commerce: an agent-based simulation approach	Journal of Simulation
8	2024	Kettele, et al. (2024)	Assessing operational resilience in food supply chains: a discrete-event simulation approach based on a framework for integrated decision-making	Journal of Simulation
9	2023	Gailan Qasem, et al., (2023)	A simulation-optimisation approach for production control strategies in perishable food supply chains	Journal of Simulation
10	2023	Barbosa, et al. (2023)	A hybrid simulation approach applied in sustainability performance assessment in make-to-order supply chains: The case of a commercial aircraft manufacturer	Journal of Simulation
11	2024	Lentle, et al. (2024)	Using simulation for long-term bed modelling in critical care	Journal of Simulation

S/N	Year	Author	Title	Publication Outlets
12	2023	Linnéusson & Goienetxea (2023)	Learning from simulating with system dynamics in healthcare: evaluating closer care strategies for elderly patients	Journal of Simulation
13	2022	Burns, et al. (2022)	Discrete-event simulation and scheduling for Mohs micrographic surgery	Journal of Simulation
14	2024	Coetsee & Bean (2024)	A multi-method simulation model to investigate the impact of sunflower seed segregation on silos	Simulation Modelling Practice and Theory
15	2024	Zeng, et al. (2024)	A dynamic simulation framework based on hybrid modeling paradigm for parallel scheduling systems in warehouses	Simulation Modelling Practice and Theory
16	2020	Hong, et al. (2020)	Evaluation of bunker size for continuous/discrete flow systems by applying discrete event simulation: A case study in mining	Simulation Modelling Practice and Theory
17	2019	Farsi, et al. (2019)	A modular hybrid simulation framework for complex manufacturing system design	Simulation Modelling Practice and Theory
18	2024	Becerra-Fernandez, et al., (2024)	Assignment-simulation model for forklifts in a distribution center with aisle constraints	Simulation Modelling Practice and Theory
19	2022	Sung, et al. (2022)	Optimizing mix of heterogeneous buses and chargers in electric bus scheduling problems	Simulation Modelling Practice and Theory
20	2024	Ruiz et al. (2024)	A simulation-based approach for decision-support in healthcare processes	Simulation Modelling Practice and Theory
21	2022	Thenarasu, et al. (2022)	Development and analysis of priority decision rules using MCDM approach for a flexible job shop scheduling: A simulation study	Simulation Modelling Practice and Theory
22	2024	Bae, et al. (2024)	A data-driven agent-based simulation of the public bicycle-sharing system in Sejong city	Simulation Modelling Practice and Theory
23	2022	Tian, et al. (2022)	Hybrid modeling methodology for integrating customers' behaviors into system simulation to improve service operations management	Simulation Modelling Practice and Theory
24	2019	Smith & Srinivas (2019)	A simulation-based evaluation of warehouse check-in strategies for improving inbound logistics operations	Simulation Modelling Practice and Theory
25	2023	Fani & Bandinelli (2023)	Sustainability Assessment through Simulation: The Case of Fashion Renting	Proceedings of the Winter Simulation Conference
26	2023	Rahman, et al. (2023)	A Simulation-Based Approach for Line Balancing under Demand Uncertainty in Production Environment	Proceedings of the Winter Simulation Conference
27	2023	Neustatel, et al. (2023)	Coordination of Hospital Parking and Transportation Services: A Simulation-Based Approach	Proceedings of the Winter Simulation Conference
28	2023	Attar, et al. (2023)	Simulation-Based Analyses and Improvements of the Smart Line Management System in Canned Beverage Industry: A Case Study in Europe	Proceedings of the Winter Simulation Conference
29	2023	Remmmelts & Hübl (2023)	Hybrid Model with Discrete-Event Simulation and Repeated Machine Learning Prediction-Based Quality Inspection of Inbound Distribution Center Deliveries	Proceedings of the Winter Simulation Conference
30	2022	Ebrahim, et al. (2022)	Discrete Event Simulation for Port Berth Maintenance Planning	Proceedings of the Winter Simulation Conference

S/N	Year	Author	Title	Publication Outlets
31	2022	Abourraja, et al. (2022)	A Data-Driven Discrete Event Simulation Model to Improve Emergency Department Logistics	Proceedings of the Winter Simulation Conference
32	2023	Attar, et al. (2023)	A Simulation-Heuristic Approach to Optimally Design Drone Delivery Systems in Rural Areas	Proceedings of the Winter Simulation Conference
33	2021	Fabrin & Ferrari, (2021)	Agent-based simulation of aircraft boarding strategies considering elderly passengers	Proceedings of the Winter Simulation Conference
34	2021	Fabrin & Ferrari (2021)	Measuring proximity of individuals during aircraft boarding process with elderly passengers through agent-based simulation	Proceedings of the Winter Simulation Conference
35	2021	Welling, et al. (2021)	Identifying potentials and impacts of lead-time based pricing in semiconductor supply chains with discrete-event simulation	Proceedings of the Winter Simulation Conference
36	2020	Renteria-Marquez, et al. (2020)	A heijunka study for automotive assembly using discrete-event simulation: a case study	Proceedings of the Winter Simulation Conference
37	2020	Rashid, et al. (2020)	Optimizing labor allocation in modular construction factory using discrete event simulation and genetic algorithm	Proceedings of the Winter Simulation Conference
38	2019	Andreasson, et al. (2019)	Utilizing discrete event simulation to support conceptual development of production systems	Proceedings of the Winter Simulation Conference
39	2019	Berg & Vandenbrink (2019)	Using simulation to evaluate provider scheduling heuristics in specialty outpatient clinics	Proceedings of the Winter Simulation Conference
40	2019	Mousavi, et al. (2019)	Simulation-based analysis of the nervousness within semiconductors supply chain planning: insight from a case study	Proceedings of the Winter Simulation Conference
41	2019	Gerrits, et al. (2019)	Simulation of real-time and opportunistic truck platooning at the Port of Rotterdam	Proceedings of the Winter Simulation Conference
42	2020	Guo, et al. (2020)	Using discrete-event simulation to find ways to reduce patient wait time in a glaucoma clinic	Proceedings of the Winter Simulation Conference
43	2021	Viana, et al. (2021)	Assessing resilience of medicine supply chain networks to disruptions: a proposed hybrid simulation modeling framework	Proceedings of the Winter Simulation Conference
44	2022	Diaz, et al. (2022)	Simulated-Based Analysis of Recovery Actions under Vendor-Managed Inventory Amid Black Swan Disruptions in the Semiconductor Industry: A Case Study from Infineon Technologies AG	Proceedings of the Winter Simulation Conference
45	2022	Lang, et al. (2022)	Decision-Making Impacts of Originating Picking Waves Process for a Distribution Center Using Discrete-Event Simulation	Proceedings of the Winter Simulation Conference
46	2023	McConville, et al., (2023)	A Hybrid Simulation of Product Reconditioning: A Case Study	Proceedings of the Winter Simulation Conference
47	2023	Chari, et al. (2023)	Modeling Risk Prioritization of a Manufacturing Supply Chain Using Discrete Event Simulation	Proceedings of the Winter Simulation Conference
48	2024	Assaf, et al. (2024)	A Hybrid Simulation-Based Optimization Framework for Managing Modular Bridge Construction Projects: A Cable-Stayed Bridge Case Study	Proceedings of the Winter Simulation Conference

S/N	Year	Author	Title	Publication Outlets
49	2022	Smith & Dickinson (2022)	Discrete-Event Simulation and Machine Learning for Prototype Composites Manufacture Lead Time Predictions	Proceedings of the Winter Simulation Conference
50	2020	Serrano-Hernandez, et al. (2020)	Agent-based simulation improves E-grocery deliveries using horizontal cooperation	Proceedings of the Winter Simulation Conference
51	2020	Allgeier, et al. (2020)	Simulation-based evaluation of lot release policies in a power semiconductor facility: a case study	Proceedings of the Winter Simulation Conference
52	2020	Garcia-Vicuña, et al. (2020)	Planning ward and intensive care unit beds for covid-19 patients using a discrete event simulation model	Proceedings of the Winter Simulation Conference
53	2023	Jin, et al. (2023)	Effects of workload on medication administration errors in nursing: an analysis based on system dynamics modeling	SIMULATION
54	2021	Wang, et al. (2021)	Policy Analysis and Implementation Impact of government subsidies on shared-bikes operation mode using system dynamics methodology: A case of Mobike in China	SIMULATION
55	2019	González-Hernández, et al. (2019)	Relocation of the distribution center of a motor oil producer reducing its storage capacity: A case study	SIMULATION
56	2022	Jen, et al. (2022)	A discrete-event simulation tool for airport deicing activities: Dallas-Fort Worth International Airport	SIMULATION
57	2024	Zhang & Tan (2024)	A data-driven approach of layout evaluation for electric vehicle charging infrastructure using agent-based simulation and GIS	SIMULATION
58	2022	Shoaib & Ramamohan (2022)	Simulation modeling and analysis of primary health center operations	SIMULATION
59	2023	Aboueljinane et al. (2023)	A discrete simulation-based optimization approach for multi-period redeployment in emergency medical services	SIMULATION
60	2022	Fava, et al. (2022)	Effect of different patient peak arrivals on an emergency department via discrete event simulation: a case study	SIMULATION
61	2021	Sadeghi, et al. (2021)	Evaluation of rail terminals in container ports using simulation: A case study	SIMULATION
62	2022	Özkan, et al. (2023)	A simulation model for evaluating the cargo transfer alternatives in liquid cargo terminals	SIMULATION