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Using simulation modelling to transform hospital planning and management to address health inequalities

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ABSTRACT

Health inequalities are a perennial concern for policymakers and in service delivery to ensure fair and equitable access and outcomes. As health inequalities are socially influenced by employment, income, and education, this impacts healthcare services among socio-economically disadvantaged groups, making it a pertinent area for investigation in seeking to promote equitable access. Researchers widely acknowledge that health equity is a multi-faceted problem requiring approaches to understand the complexity and interconnections in hospital planning as a precursor to healthcare delivery. Operations research offers the potential to develop analytical models and frameworks to aid in complex decision-making that has both a strategic and operational function in problem-solving. This paper develops a simulation-based modelling framework (SimulEQUITY) to model the complexities in addressing health inequalities at a hospital level. The model encompasses an entire hospital operation (including inpatient, outpatient, and emergency department services) using the discrete-event simulation method to simulate the behaviour and performance of real-world systems, processes, or organisations. The paper makes a sustained contribution to knowledge by challenging the existing population-level planning approaches in healthcare that often overlook individual patient needs, especially within disadvantaged groups. By holistically modelling an entire hospital, socio-economic variations in patients' pathways are developed by incorporating individual patient attributes and variables. This innovative framework facilitates the exploration of diverse scenarios, from processes to resources and environmental factors, enabling key decision-makers to evaluate what intervention strategies to adopt as well as the likely scenarios for future patterns of healthcare inequality. The paper outlines the decision-support toolkit developed and the practical application of the SimulEQUITY model through to implementation within a hospital in the UK. This moves hospital management and strategic planning to a more dynamic position where a software-based approach, incorporating complexity, is implicit in the modelling rather than simplification and generalisation arising from the use of population-based models.

1. Introduction

The analysis of health inequalities is a long-standing tradition in social science, ranging from the global to local scale, for which a diverse array of disciplinary approaches have been developed to understand why disparities exist in accessing healthcare, its delivery and impact on achieving healthcare policy outcomes. While these inequalities may represent a 'wicked problem', in that they are societal issues with multiple complexities that are not easily solvable (Rittel and Webber, 1973), social science has pursued more interdisciplinary, interconnected, and synthesizing approaches that can accommodate the complexity of such societal problems. Systems modelling has emerged as one method of problem-solving in health research, as Chang et al. (2017) and Mahamoud et al. (2013) illustrate. As Kielmann et al. (2022) explain, 'the idea of the health system as interconnected, complex, dynamic, and driven by human actions and values has shifted the focus from quantifying inputs and outputs to understanding health systems processes, mechanisms, and levers for systems change and improvement'. This approach enables us to recognize and model the interconnections between the factors that may contribute to health inequalities, such as socio-economic status (SES) (Marmot et al., 2010; Shavers, 2007), ethnicity, or geographical location. Theoretical research from political economy and sociology also illustrates some of the more socially determined interconnecting factors that compound inequality in

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healthcare, and which are exacerbated by employment status and level of income and education. Therefore, in seeking to address one fundamental question that underpins the inequality in health research globally – who gets what, where, and why? – we need to utilize novel synthesizing research methodologies that can depict the problem and possible solutions.

Conceptually, SES is an important complicating factor in health inequalities, as it affects disease incidence, severity, and access to healthcare settings (Shavers, 2007). This connection was validated by an OECD longitudinal study in which individuals who attained higher levels of education typically experienced enhanced health and longer life expectancy (Raghupathi and Raghupathi, 2020). Similarly, in the USA, structural inequalities (e.g., racism, and sexism) were linked to poor health for black women (Homan et al., 2021). A systematic review by Green et al. (2021) revealed that COVID-19 had disproportionately impacted vulnerable populations, especially those coming from racial minorities and those with low incomes, ultimately resulting in their having limited access to services. Both over- and underutilization of healthcare services among socio-economically disadvantaged groups can contribute to worsening healthcare inequities. Where healthcare services are overutilized without appropriate hospital resources being in place, existing inequities can be exacerbated (Asaria et al., 2016). Conversely, barriers to access leading to underutilization within these groups can also worsen healthcare inequities (Heaton et al., 2016).

1.1. Hospitals as a focus for reducing health inequalities

Policy research acknowledges that a multifaceted, multi-agency approach is required to tackle health disparities and that this should be done through strategies including innovative healthcare policies and resource allocation, workforce diversity, and community engagement (Asthana and Gibson, 2008), including hospital planning (Leonard et al., 2023). Strategic hospital planning involves comprehensive assessment, optimal allocation, and management of resources within hospital settings to optimize healthcare delivery and improve patient outcomes by leading to reduced waiting times and enhanced healthcare quality for all patients, especially those who are most at risk or vulnerable (Dong, et al., 2020; Cunningham et al., 2022).

One aspect of hospital planning that has gained attention is workforce planning, particularly in terms of appropriate staffing levels and the skill mix of healthcare professionals (Pittman, et al., 2021). Driscoll et al. (2013) demonstrated how intentional workforce planning in hospitals, for example by ensuring adequate nurse staffing levels are maintained, can reduce disparities in patient outcomes and experiences. By having a diverse and culturally competent healthcare workforce, hospitals can better meet the unique needs of different patient populations, thus promoting equity in healthcare delivery. Targeted investment in underserved areas, for example by directing additional resources and infrastructure to high concentrations of vulnerable populations, can enhance accessibility and reduce disparities in healthcare provision (Asaria, et al., 2016). As anchor institutions in local communities, hospitals clearly provide a pivotal role in reducing spatial and social inequalities, so research approaches that can synthesize and incorporate the factors and levers that can enact change are widely sought within healthcare systems. These systems are seeking to maximize resource efficiency in relation to health outcomes, although the political economy of healthcare funding may impact the implementation of effective planning strategies and the equitable distribution of resources by hospital planners.

1.2. Modelling hospitals and health provision

Love-Koh et al. (2020) outlined the tools and methods that have been developed to incorporate equity into health resource allocation. Resource utilization often relies on various key metrics, such as the frequency of primary care visits and hospital admissions (Lueckmann, et al., 2021), to establish the correlation with SES. Several models, including economic approaches, have been developed to reduce health disparities in six key domains:

1) Benefit incidence analysis (BIA) assesses the imbalance in the allocation of financial resources by examining how public healthcare spending is distributed among various social groups (Mills, et al., 2012). BIA calculates the portion of added advantage gained by certain members of the society, often considering their SES as a factor.
2) Marginal BIA examines how increased spending affects different social groups in terms of benefits and resource allocation over time and regions (Younger, 2003). It assesses the effect on the distribution of benefits caused by expenditure changes and potential losses.
3) Mathematical formulas allocate resources based on the health requirements of different geographic regions and local populations. This methodology establishes the definition of need by considering the past demand for services, specifically in terms of healthcare utilization (Penno et al., 2013). As an approach, it is extensively employed worldwide, including in countries such as the UK (The Kings Fund, 2013), South America, and low- to middle-income countries (LMICs) (Briscombe et al. (2010); Anselmi et al. (2015); Manthalu et al. (2010)).
4) Health benefits packages (HBPs) are a substitute to the traditional mathematical formulas in resource-constrained settings (Glassman et al., 2016). HBPs estimate the health resources needed by linking service delivery costs with projected patient populations. In Malawi, household survey data provided disease rates across patient groups, guiding intervention-cost integration. This influenced resource allocation in four of Malawi's 28 districts (Ochalek, et al., 2018).
5) Health systems reform may lead to the implementation of cost-effective initiatives, such as community-based interventions and primary care programmes (Carrin et al., 2005).
6) Extended cost-effectiveness analysis (ECEA) and distributional cost-effectiveness analysis (DCEA) are widely used economic techniques that incorporate factors such as health benefits and opportunity costs. ECEA holds a particular significance in LMIC settings, as it assesses the extent of financial protection against unexpected expenses and the mitigation of private expenditures through interventions funded by public budgets (Verguet et al., 2016). On the other hand, DCEA focuses on two key aspects: the impact of an intervention and its effects on disparities in health (Asaria et al., 2015). Prior to the intervention, DCEA models health inequality; it then estimates the hypothetical distribution post-intervention, so that the impact can be assessed accordingly.

While existing studies often assume a 'one size fits all' approach, their strength lies in the simplicity of modelling, particularly in their economic and mathematical aspects (e.g., using Excel spreadsheets). However, these approaches fail to consider the broader system in the context of health inequalities. Furthermore, current models do not account for the significant individual patient diversity that may exist, particularly within socio-economically disadvantaged groups. This limitation is evident when assessing resource utilization in a hospital setting, including follow-up visits, admissions, length of stay (LoS), costs, bed and clinic usage, and healthcare worker allocation. These metrics vary widely, both across different departments and specialties within a hospital and within the broader population. Allocating resources solely based on population-level data is overly simplistic and lacks sophistication and precision.

A more innovative framework, based on a holistic modelling approach, is required to address health inequalities so as to capture the complexity of healthcare systems and how they operate and are managed. To implement such an approach in hospital planning, these organisations need to be equipped with the financial, human, and non-human resources to understand and target those inequalities. This article develops an innovative simulation-based modelling framework that can fulfil these hospital planning objectives. The framework enables planners and managers to pose and answer crucial questions related to addressing health inequities, and supports key decision-makers (KDMs) in six critical directions:

1) Optimization of Resource Allocation: The simulation-based modelling framework aims to assist decision-makers in identifying the optimal allocation of the staff, beds, clinics, theatre sessions, and financial resources needed to effectively meet the healthcare demands of local populations. It takes into account the variations associated with SES, ensuring that resource allocation is aligned with the specific needs of different social groups.
2) Evaluation and Impact of Intervention Strategies: The modelling framework is capable of evaluating the potential impact of various intervention strategies aimed at reducing health inequalities. Decision-makers can utilize the model to assess the effectiveness of interventions such as targeted healthcare programmes, community outreach initiatives, preventive measures, and policy changes. This allows for the use of evidence-based decision-making to prioritize and implement strategies that have the greatest potential to alleviate health disparities.
3) Forecasting Future Health Inequalities: By utilizing historical data and demographic trends, the simulation model can model and forecast future health inequalities. Decision-makers can use the model's capacity to proactively plan and allocate resources in advance to implement targeted interventions and design policies that aim to eliminate the gaps in healthcare access and outcomes among different socio-economic groups.
4) Holistic Decision-Making: Our holistic approach moves our thinking beyond addressing health inequalities to include outcomes, resource utilization, and their financial implications, providing an opportunity for evaluation of specific decisions before practical implementation.
5) Capturing Uncertainty: Unlike existing methods, our approach assists in embracing uncertainty as an individual patient pathway is linked to socio-economic variations. This enhances the model's precision in addressing the complexity of health inequalities.
6) Versatility and Global Applicability: Our modelling approach develops a generic yet versatile framework that can be applied globally to different healthcare institutions. It can be extended to integrate wider components of local care, such as primary care, community services, and the voluntary sector, known for its active role in addressing health inequalities.

The article commences with a discussion of our framework, *SimulEQUITY*, and presents a case study on the use of our simulation-based modelling framework within a National Health Service (NHS) Trust in the UK. The framework is designed to be adaptable and can be implemented in various hospital settings worldwide.

2. SimulEQUITY: a simulation-based modelling framework for addressing social disparities

Various methods and approaches are utilized in healthcare modelling (Laker, et al., 2018), many of which have been developed in the field of operations research. The method selected is contingent upon the healthcare problem and system context (Mielczarek, 2016). Agent-based simulation (ABS), which concerns the action and interaction of agents (individuals), is commonly used to model infectious diseases (Codella et al., 2015). Discrete-event simulation (DES) is used for operational modelling of hospital departments (Tanantong et al., 2022). Monte Carlo simulation (MCS) is utilized for predicting disease progression and burden (Zafari et al., 2021). System dynamics (SD) focuses on the cause-effect relationship and is mostly applied to analyse national-level policy changes (Mwanza, et al., 2022).

The DES method is widely used to model complex systems like hospitals (Vázquez-Serrano et al., 2021). This approach has proven effective in constructing patient-level models that accurately track patients' individual movements. It allows for the assignment of attributes such as SES, age, and severity of the health condition at each step along the patient pathway. Notably, other methods do not offer the level of granularity required for this type of modelling. SD is a strategic and high-level technique and ABS is typically used in population-based modelling, so these methods are not ideally suited to patient-centred applications. However, DES is the most suitable method for capturing patient pathways and their duration (i.e., time), so it is more advantageous over other forms of operational modelling. Consequently, DES was selected as the preferred methodology for this study after reviewing the available methods.

Numerous DES frameworks have emerged within the literature, each tailored to diverse objectives (Banks et al., 2005; Boyle et al., 2022). As this study focuses on social disparity reduction, we develop a novel framework using the process advocated by Banks et al. (2005). The approach is highly data-driven, integrating hybrid methodologies, including demand forecasting for the entire range of hospital services.

The SimulEQUITY framework develops a simulation model, which functions as a tool aimed at addressing health inequalities. The tool assists decision-makers in understanding the potential impact of scenarios and interventions on health inequalities before implementation in the real world. The users can test the pre-set scenarios in the tool, such as demand-capacity changes, and providing transportation or create custom scenarios. In addition, the baseline scenario provides a clear picture of the current situation in the setting (e.g., in terms of activities by socio-economic status) to help users diagnose the problem.

The SimulEQUITY framework comprises ten sequential steps (see Fig. 1), systematically categorized into three main parts: (I) system analysis, (II) input settings, and (III) model development. We provide a comprehensive step-by-step guide to the framework's development process. While the traditional steps are outlined, our emphasis is on the innovative aspects of the SimulEQUITY framework, including the pivotal steps (namely, conceptualization, data preparation, patient attributes, and parameter estimation), which are further developed later in this paper.

2.1. Part I: system analysis

Step 1. Problem and Objectives: Investigate the problem in the system (e.g., health inequalities) and establish the objectives of the study to address the concerns (e.g., by increasing resources) using SimulEQUITY to identify the interventions and scenarios that could potentially be evaluated and implemented in practice.

Step 2. Conceptualization: Meetings are held with key stakeholders as focus groups to capture intricate detail of the patient pathway – a process known as *conceptualization* – and the outputs are defined (i.e., key performance indicators). Fig. 2 illustrates the patient flow within a hospital setting, including the emergency department (ED), inpatient services, and outpatient services, which can be generalized globally. Each service is colour-coded in Fig. 2 for ease of differentiation (i.e., red for ED, orange for inpatient services, and blue for outpatient services).

Typically, patients arrive at the ED via ambulance or walk-in, or are referred from another healthcare setting (e.g., general practitioners (GPs)) or self-refer when out-of-hours care is unavailable. Patients are registered and triaged by a nurse; then, a doctor carries out diagnostic procedures and any required treatment. During each step of this process, patients will experience wait times (e.g., for treatment); the length of these is mainly determined by the urgency of their condition and the time needed until necessary resources (beds/cubicles, doctor, nurse) and test results are available. After the treatment has been concluded, a discharge process is initiated. Patients may either continue their care by

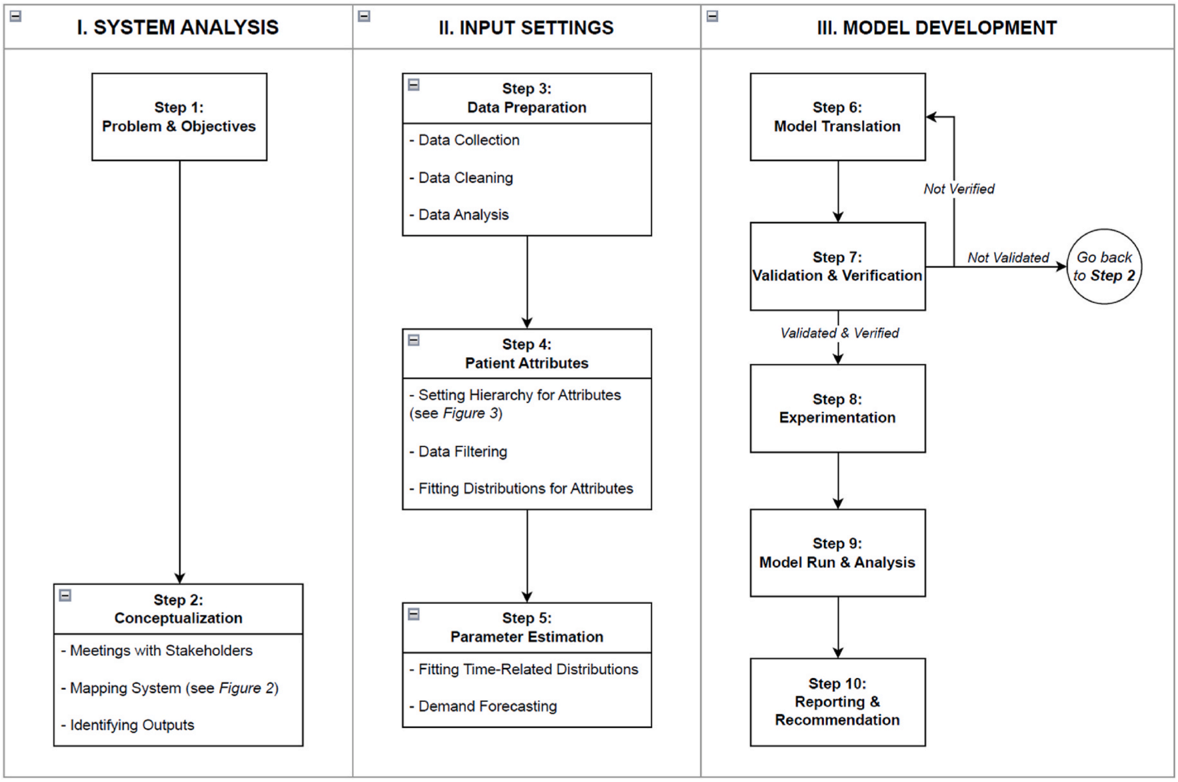

Fig. 1. SimulEQUITY framework.

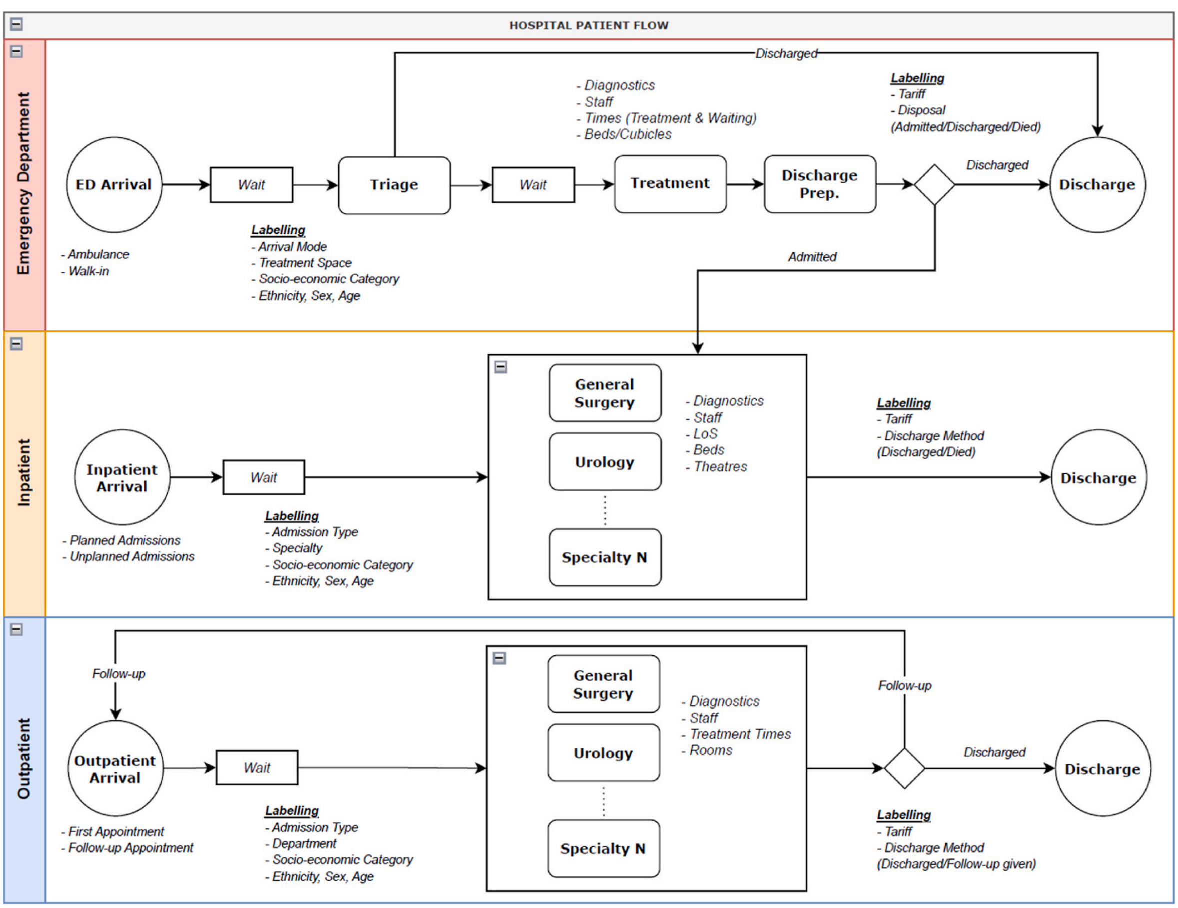

Fig. 2. Generic hospital patient flow. ED: Emergency Department, LoS: Length of Stay.

being admitted to inpatient services or be discharged, either in a stable condition or as a result of their death.

Inpatient admissions come in two forms: planned ('elective' in the UK) and unplanned (non-elective). In planned admissions, patients are referred to specialty services, like general surgery or urology, either by a GP or a consultant. There can be waiting times of weeks, months, or even years for these appointments. Unplanned admissions occur when patients are admitted as emergencies via the ED or referrals from other healthcare providers. Inpatient procedures take place within the relevant specialty, using resources such as beds, operating theatres, and staff. LoS varies based on the patient's condition, ranging from same-day discharge to several days in the hospital.

Patients are referred to outpatient services by GPs, consultants, or other healthcare providers. Outpatient appointments (termed 'attendances' within the NHS), whether initial visits or follow-ups, are typically scheduled well in advance, leading to potentially long waiting times. After an initial diagnostic routine, patients consult with a specialist in a clinic room. Following this consultation, patients are either discharged or given a follow-up appointment. It is important to note that all patients leave on the same day, without requiring an overnight stay.

The conceptualization process is pivotal, serving as the foundation for adapting the framework to account for these variations before development commences. During the conceptualization phase, careful consideration must be given to the unique characteristics of the healthcare setting under investigation. This involves a comprehensive assessment of cultural nuances, socio-economic factors, and prevailing health policies. This framework is designed to be flexible, allowing for customization based on the specific context in which it will be applied.

The key resources for each specialty, such as beds, staff, and treatment time, are outlined in Fig. 2, alongside the corresponding treatment locations. Our patient flow diagram is adaptable, allowing specialties or departments to be added or removed as required. Patients will be categorized based on SES and other characteristics (e.g., age, cost of care) at each stage, distinguishing between individual patients. We also include statistical distributions of data (for each SES) to represent system variability in hospitals accurately. Further details are given in the following sections.

2.2. Part II: input settings

Step 3. Data Preparation: Thorough data preparation is vital to developing a data-driven simulation model focused on addressing social inequalities. This involves collecting patient-level data from sources such as hospital databases, national data sets, expert opinions, or published studies. These data sets encompass topics such as demand for services, patient routing, patient characteristics (e.g., SES), resources, cost, and time-related activities. The data should be patient-level and must include SES data to effectively address social disparities.

Meticulous data cleaning, especially in big data analytics, is crucial for identifying and rectifying issues such as duplicated or outlier data. Additionally, addressing missing or incomplete data is of utmost importance as it poses a significant risk to the reliability of the model. A systematic approach, such as excluding related observations from estimations, should be employed. Failure to consider and provide for these aspects may result in unrealistic and less interpretable model results, particularly for health inequalities. Once data cleaning is complete, the next step is data analysis to determine patient characteristics and establish statistical distributions.

The accuracy of SimulEQUITY is contingent on the availability and quality of data, acknowledging the potential impact of data limitations on precision. We also acknowledge the sensitivity of SES categorization and its potential biases. Users should employ patient-level local/national data with standardized SES for a reliable and meaningful output. The use of data from different sources or with inconsistent SES categories may result in unrealistic or unreliable outputs. Additionally, challenges in diverse healthcare environments stem from differences in data availability and quality.

Step 4. Patient Attributes, when systematically assigned, are crucial in terms of capturing social disparities in healthcare systems. This necessitates a focus on SES as a central factor in data analysis and attribute assignment. Existing research often lacks a clear structure for labelling patients using the DES approach, resulting in the selection of attributes and variables without a specific sequence and a limited consideration of the relationships between different characteristics. However, patients' characteristics and their healthcare system interactions can vary according to their SES, leading to differences in resource utilization, such as LoS, between individuals who are deprived and more affluent.

Therefore, we proposed a stepwise labelling approach and developed a structural hierarchy (see Fig. 3). The hierarchy consists of four levels that can be adjusted if needed. In *Level I*, we look at the percentage of patients who came in as appointments for outpatient care, admissions for inpatient care, and those who arrived at the ED. In *Level II*, we assign a specific department or specialty based on how the patient entered (like their first appointment (FA)).

Level III is the key point in the hierarchy (Fig. 3) as socio-economic categories are incorporated. At Level III, SES is assigned for each department/specialty. SES is grouped from most deprived (low) to least deprived (high), using an index of multiple deprivation (IMD). The number of socio-economic index (SI) categories as well as domains of deprivation and their weightings may differ by country. For example, while the English version of the IMD (GOV.UK, 2019) consists of seven determinants, such as employment, health, and income, the Canadian version (Statistics Canada, 2019) has four domains.

In *Level IV*, the patient attributes, variables, distributions, and other factors (time-related activities and routing options) are assigned based on SES. This hierarchy is adaptable, allowing for the inclusion of additional variables like waiting time and cost of care, and the option exists to add more focused levels, such as ethnicity, for more detailed models if necessary.

Percentages and statistical data distributions for all patient attributes and variables, from *Level I* to *Level IV*, can be established following the hierarchy and sequence of the structure. For example, for FAs in outpatient services, we calculate percentages for each specialty (e.g., x1% for general surgery, x2% for urology). Then, we determine percentages for specific SI categories within each specialty (e.g., within urology, y1% for SI category 1, y2% for SI category 2).

In *Level IV*, we analyse statistical data related to patient characteristics such as ethnicity, sex, and age, as well as different activities like discharges, referrals, and costs. We do this for each SI category because each category might have different patterns for these patient characteristics and activities. To do this, we calculate percentages and distributions for each characteristic or variable. For instance, if there are five SI categories, we create five distinct statistical distributions for ethnicity for patients who have their FA in the urology specialty. We repeat this for all other medical specialties, different types of appointments, and various departments, like inpatient care and the ED.

Step 5. Parameter Estimation: Statistical methods are used to estimate time- and demand-related parameters in DES, which includes waiting time, LoS, and treatment times. These parameters are set either using fitted frequency or theoretical distributions for each SI category. For instance, LoS may follow a log-normal distribution for less deprived patients in cardiology, while a gamma distribution may be used for more deprived patients. This approach helps users to address socio-economic differences and create a more realistic model.

Quantitative forecasting methods can be used to predict the demand for inpatient services, outpatient services, and ED visits. This prediction holds significant importance as it serves as a vital input for the model, a central component of the SimulEQUITY framework. The accurate

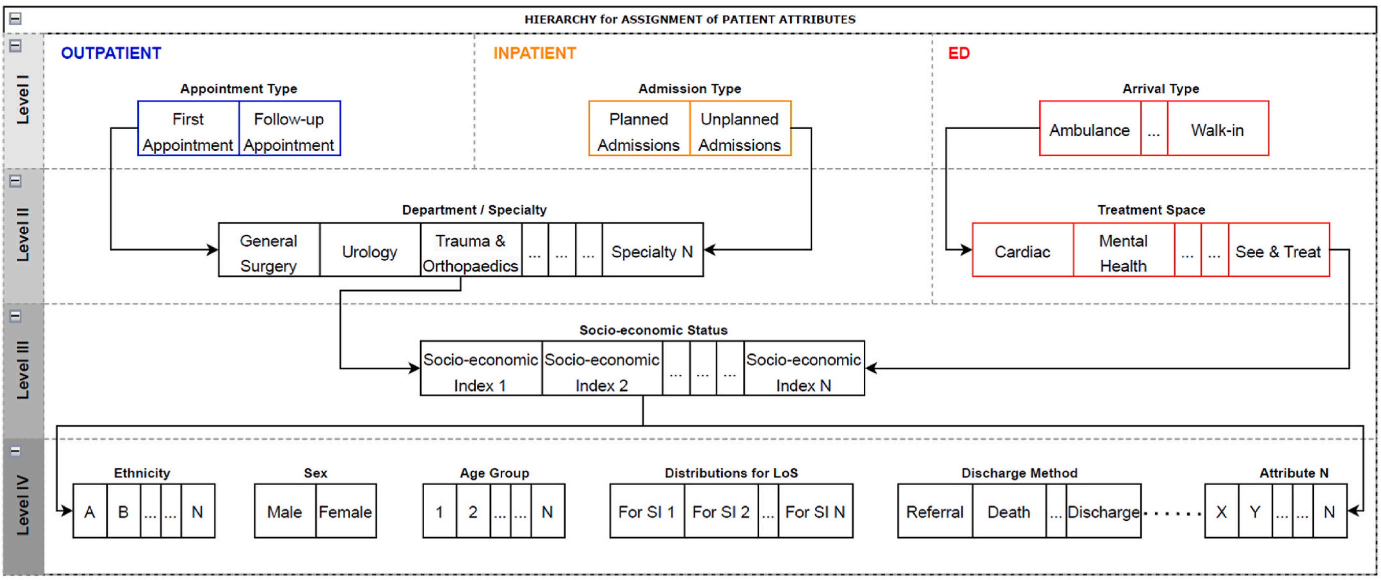

Fig. 3. Hierarchy for assignment of patient attributes and model variables. ED: Emergency Department, SI: Socio-economic Index.

estimation of future service demand for the entire hospital, categorized by medical specialties, age groups, and service types (inpatient, outpatient, ED), is of the utmost importance in terms of ensuring reliability and precision.

Separate forecasts are needed for unplanned admissions, planned admissions, and appointment outcomes, including cancellations and missed appointments. This requires the development of multiple models for each medical specialty. To accomplish this, multiple linear regression (MLR), autoregressive integrated moving average (ARIMA), Seasonal and Trend decomposition using Loess Function (STLF), and exponential smoothing (ES) are the most popular quantitative methods. The software R with libraries auto. arima(), ets(), stlf(), and stepAIC() can be utilized for this purpose. The best forecasting method can be chosen using the mean absolute scaled error criterion, ensuring optimal selection (Ordu et al., 2020).

Patient admissions and appointments are influenced by a myriad of unpredictable factors, including epidemics, policy changes, and shifts in population health trends. SimulEQUITY is inherently equipped to capture and simulate a wide range of unpredictable factors, enabling KDMs to evaluate intervention strategies under various conditions, including those influenced by epidemics, policy changes, and shifts in population health trends.

The remaining steps (Step 6–10), which are in Model Development (Part III), are explained in Appendix 1.

3. SimulEQUITY in practice

This SimulEQUITY framework was applied to an NHS Trust in England serving a local population of around 500,000 people and employing over 3500 staff. The aim was to validate the framework and demonstrate its usefulness in determining the optimal resource allocation and predicting future health inequities as well as identifying the necessary resources (such as beds, theatres, clinics, and staff) that are essential to deliver timely treatment.

3.1. The decision-support tool

A user-friendly decision-support tool (DST) was created to enhance hospital planning and address health inequities by ensuring that essential resources are available when needed. It aims to tackle the problem of unequal access to both treatment (i.e., *Step 1* in SimulEQUITY) and support caused by disparities in health service quality, which in turn are due to insufficient funding and the fact that resources are spread between different locations (The Health Foundation, 2023). The tool's primary application targeted a prominent NHS Trust in England, yet its adaptability extends globally. The DST also aims to drive positive changes amid critical challenges like workforce shortages, extended waiting lists, labour disputes, and post-COVID recovery efforts. To ensure user-friendly accessibility and to enable non-experts to run simulations independently, an intuitive graphical user interface was developed for end users. The dashboards facilitate the exploration of specific medical specialties (see Fig. 4), enabling effortless navigation and tailored output generation.

Furthermore, the DST surpasses hospital specialty boundaries, facilitating the assessment of interdependencies and bottlenecks across diverse areas. This holistic approach allows for a comprehensive evaluation of overall hospital performance and optimization opportunities. The user-friendly interface offers Excel-based input modifications for flexibility, accommodating a range of parameters like activity-related inputs, care pathways, staff, and resources, accounting for socio-economic variations (e.g., IMD).

The DST presents two patient pathway configurations: the current service scenario and an intervention-driven scenario. It calculates key metrics like required bed capacity, theatre and clinic utilization, and staff requirements, all longitudinally (e.g., over five years), and offers a plethora of output formats including graphical and numerical displays via Excel files.

In addition to resource estimations, the DST provides comprehensive financial reports for ED, inpatient, and outpatient services at specialty level broken down by socio-economic variations. This enhances its utility for strategic decision-making by enabling the allocation of extra financial resources to regions with more disadvantaged populations or differences in care quality for their local residents. This evidence, presented through the DST in the form of a business case, assists in conveying the economic case for additional support and the outcomes.

3.2. Hospital layout and patient flow

The participative modelling (PM) approach was utilized to involve key stakeholders and gather relevant information to develop a patient pathway model *(Step 2)*. Stakeholders from the hospital, comprising senior directors, consultants, and nurses, contributed to outpatient, inpatient, and ED pathway discussions, assessing potential change scenarios through the PM approach. An updated model was presented at a

Fig. 4. Paediatric specialty dashboard.

workshop. Access to care involved ED visits, inpatient admissions, and outpatient attendances. ED arrivals comprised walk-ins, NHS 111 referrals (available in England as a digital triage system people call that asks about your symptoms and directs patients to the most suitable service such as treatment at an ED), ambulance handovers, primary care doctor referrals, and community care. Patient triage determines care urgency and resource availability.

Allocation of resources, such as beds and staff, was managed during inpatient admissions, outpatient attendances, and transfers for all specialties. Outpatient services encompassed consultations, diagnostics, and therapies, categorized as FA or follow-up. The Simul8 simulation tool (Simul8 Corporation, 2022) was employed to simulate patient flow and resource allocation. While the simplified diagram showcased inpatient, outpatient, and ED pathways, it could not encompass the intricate operational intricacies due to the inherent complexity of a hospital system and the necessity for a globally applicable model, not limited to the NHS. Inpatient and outpatient services were presented as streamlined processes in recognition of this need for a simplified depiction. Therefore, balancing inclusion and exclusion, we made careful choices regarding detail level to align with evaluating resource utilization, making sure individual patients' key demographics and characteristics, such as socio-economic variation, age, ethnicity, and sex, were embedded and captured in the model.

3.3. Data, analysis, and input parameters

During the financial year April 2021 to end of March 2022, the hospital experienced a total of 73,955 admissions for inpatient care, 384,750 instances of outpatient attendance, and 120,930 visits to the ED *(Step 3)*. The hospital provided data apart from that concerning costs and SES; for the latter categories, an IMD was used, with information extracted from the national data set known as Hospital Episodes Statistics (HES). HES is an extensive collection of electronic medical records derived from NHS hospitals in England (NHS Digital, 2023).

The IMD is a measure of the level of deprivation in different geographical areas, and in England IMD is linked to patient records in HES, which helps provide researchers with an understanding of how socio-economic factors influence healthcare utilization and outcomes. The IMD is grouped into quantiles (five groups) with IMD 1 denoting the most deprived category, while IMD 5 corresponds to the least deprived category.

For each specialty, 33 input parameters were derived and estimated from diverse categories *(Step 4)* such as demand, staffing, bed and clinic capacity, revenue, and annual session capacity in operating theatres, alongside 30 IMD-related parameters (63 in total for each specialty), excluding forecast activity over the simulation period (five years). An operating theatre session could accommodate one or more patients at a time for surgery. Each data category is categorized based on inpatient admissions (elective and non-elective) and outpatient attendances (FAs and follow-ups). A total of 630 inputs for 10 specialties (10 multiplied by 63) are estimated, including statistical data distributions to capture fluctuations and uncertainties *(Step 5)*. For instance, for the paediatrics specialty, the average waiting time for an elective admission is 126 days, and a log-normal distribution best fits the waiting time distribution based on the available data. Moreover, future service demand (i.e., five years, from 2023/24 to 2027/28) for the entire hospital is forecast using ARIMA, ES, MLR, and STLF methods, as described above.

Demand forecasting enables future activities in ED, inpatient, and outpatient services to be predicted. The nuances of health inequality, such as socio-economic factors and demographics, are considered during the simulation phase dynamically adjusting demand as the simulation runs. This adjustment is a key strength of SimulEQUITY, as it allows the model to account for the complexities and interconnections inherent in hospital planning, particularly in addressing health inequalities. As the simulation progresses, the impact of health inequality factors on key metrics, including the utilization of resources and healthcare outcomes, is actively captured.

Parameters are meticulously estimated using robust statistical techniques. The data fitting process is carried out using the R software, employing specialized distribution fitting libraries. This involves a systematic approach wherein various probability distributions are tested against the empirical data. The selection of the best-fitting distribution is determined by ranking the 'goodness of fit' values derived from the results.

To convey the substantial magnitude of the estimated parameters, we present, as an example in Appendix 2, that comprises a comprehensive list of estimated parameters specific to the paediatric specialty. The inputs around patient characteristics and routing regarding paediatrics are provided in Tables S1 and S2 in the supplementary file. This is replicated for all the remaining specialties, namely cardiology, ophthalmology, trauma and orthopaedics, general surgery, general medicine, gastroenterology, gynaecology, urology, and obstetrics and midwifery.

Based on the IMD analysis, the second-most socio-economically disadvantaged category (i.e., IMD 2) had the greatest volume of inpatient admissions, outpatient attendances, and ED visits across all the specialties. The example of paediatrics (Table A1) indicated that 34.47% of elective admissions were attributed to this demographic. The average

LoS for these patients was 3.3 days, which marginally exceeds those in Groups 3, 4, and 5 (considered least deprived), yet remains lower than that of the patients in Group 1 (considered most deprived), who have an average LoS of 4 days.

The hospital's total revenue is linked to the Healthcare Resource Groups' (HRGs') tariffs, which significantly influence its finances. An HRG Code is assigned to each patient, which is aligned with the 2022/23 National Tariff Payment System (NHS England, 2022), signifying the cost of care in pound sterling. HRG tariffs in the NHS are like price tags for medical care. They group treatments and services based on how complicated and expensive they are. This helps ensure hospitals and healthcare providers are paid fairly for the care they give. It is a way to make sure everyone gets the right amount of money for the care provided/received. Lastly, the conceptual model with input settings is translated into a computer simulation model using Simul8 software *(Step 6)*. Verification and validation *(Step 7)* of the model are explained in Appendix 1 in detail.

3.4. Results

To illustrate the practical use of SimulEQUITY in day-to-day decision-making, we predict health disparities between service demand, resource utilization, and the necessary requirements. We assess the potential ramifications that different scenarios could impose on the hospital's operations from 2023 to 2027. To facilitate a smooth transition and effective utilization of SimulEQUITY, regular stakeholder focus group meetings were organized. These meetings involved KDMs, including the senior management team comprising the Director of Strategy and Planning, Director of Performance, Director of Finance, and service managers. These stakeholders played a crucial role as end users of the tool. Collaboratively devised during the stakeholder focus group meetings, two distinct projections have been formulated *(Step 8)*:

1) **A Baseline scenario**: This scenario entails maintaining the hospital in its current state, with no alterations to existing operational protocols and patient flow.
2) **An increase in outpatient attendances and elective admissions**: In the initial two years (2023–2024), the hospital anticipated a rise in both inpatient and outpatient services performed. The main goal was to address the backlog caused by COVID-19 and gradually reduce activity in the subsequent years (2025–2027) to meet the 18-week target set by NHS England.

SimulEQUITY serves as a versatile framework, capable of being tailored to different contexts and employed to evaluate an extensive array of scenarios, but in this example, we highlight findings from the paediatrics specialism, whose patients have the greatest range of socio-economic status *(Step 9)*. Nevertheless, an identical array of results is generated by the simulation model for the remaining nine specialties. In the baseline scenario (SC1), where no changes are made, the hospital should anticipate having the following number of inpatient admissions for the paediatric specialty during the 2023–2027 period: 5,457, 5,564, 5,569, 5,625, and 5,682, respectively. On average, from 2023 to 2025, around 35 inpatient beds would be needed, and this number would increase to 36 beds for the years 2026 and 2027 to manage the demand.

The data based on IMDs, as shown in Fig. 5, indicates that the hospital provides more care to children in the second most economically disadvantaged group than to those in other categories. Specifically, the projected inpatient admissions for this group would be 2,039, 2,079, 2,081, 2,102, and 2,123, respectively. Under this scenario, the backlog of patients would compound annually, intensifying the strain on the existing backlog. Consequently, this could diminish care quality, potentially leading to adverse effects on health outcomes – especially concerning disadvantaged groups. In response, the hospital management aims to assess how an increase in elective admissions and outpatient visits might influence the existing backlog and waiting list. Consequently, in Scenario 2 (SC2), we introduce an experiment involving a 10% increase in both elective admissions and outpatient appointments across all medical specialties, including paediatrics. This increase will lead to a higher number of inpatient admissions and outpatient services rendered compared to the baseline scenario. Specifically, there will be approximately 185, 332, 565, 745, and 921 additional admissions for the years 2023 through 2027, respectively. To accommodate this increase, the hospital will require an extra two beds in 2023, three in 2024, five in 2025, six in 2026, and eight in 2027. Additional beds would necessitate extra healthcare workers, including consultants and nurses. This, in turn, adds to the workload of the current staff, who are already grappling with the overwhelming demand.

Considering that children from the second-most-deprived socio-economic category utilize beds the most, a closer examination indicates that the rise in activity will require an additional bed on average in 2023 and 2024 respectively for this group. Additionally, from 2025 to 2027, two extra beds per year will be necessary. It is also important to note that bed allocation is not determined by socio-economic factors. Providing these supplementary resources is essential to ensure that care is promptly delivered where it is required. Failure to do so could potentially exacerbate the disadvantages faced by this particular group.

A similar trend is noticeable in outpatient services. However, the

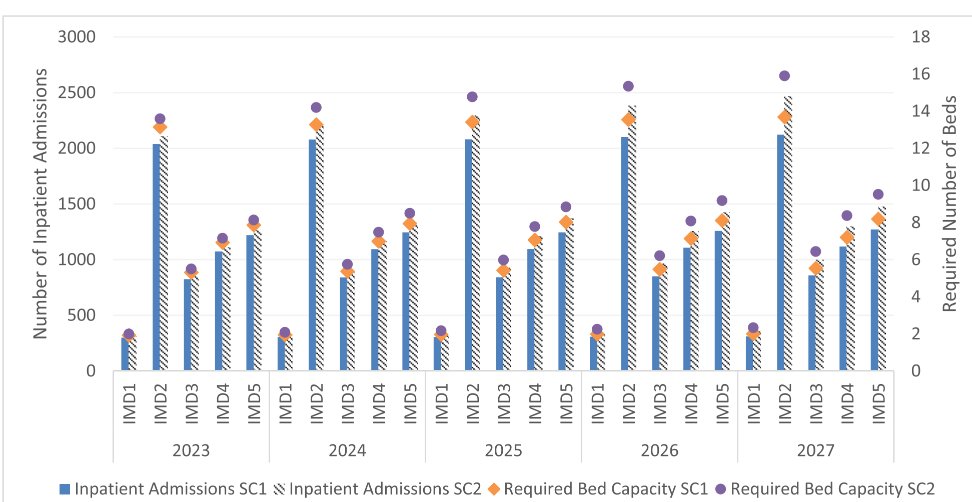

Fig. 5. Inpatient admissions and the required bed capacity for the paediatrics specialty, broken down by IMDs, comparing the two scenarios for the period 2023–2027. SC1: Scenario 1; SC2: Scenario 2; IMD: Index of multiple deprivation.

hospital is presently grappling with a challenge – its clinics are overutilized, with utilization rates exceeding 100%, due to limited capacity. The situation is often managed by borrowing clinic space from other specialties just to meet the existing demand, which would be compounded by a surge in outpatient appointments projected in SC2 *(Step 10)*.

In the baseline scenario, the hospital foresees 11,305 outpatient visits to the paediatric specialty in 2023. Over the subsequent years from 2024 to 2027, the numbers are projected as follows: 11,913, 12,617, 13,310, and 14,004, respectively. Clinic utilization rates are expected to be 153% in 2023 and 162% in 2024, escalating to 171% in 2025, 181% in 2026, and 189% in 2027.

The introduction of SC2, aimed at reducing the backlog of patients on the waiting list, further exacerbates the situation. This scenario leads to an additional 10% increase in clinic utilization in 2023, followed by 19% in 2024, 21% in 2025, 19% in 2026, and 15% in 2027.

Across both scenarios (see Fig. 6), it is important to highlight that children from the second-most-deprived socio-economic background (IMD 2) exhibit the highest utilization of the paediatric specialty, accounting for an average of 52% over the period of 4-year. This observation underscores a concerning situation for the hospital, as insufficient capacity and resources could potentially undermine the quality of care provided to these children, given that a significant portion comes from disadvantaged demographics. This aspect could potentially exert a significant influence on health outcomes. It is worth noting that early childhood care can determine the quality of outcomes later in adult life, further emphasizing the significance of addressing this issue.

Fig. 7 illustrates the overall cost of healthcare (representing the budgetary requirement for the hospital). In order to address the backlog of patients awaiting treatment while sustaining the capacity to cater to service demands, the hospital is required to increase its budget for the paediatrics specialty from £9.575 million (as depicted in Scenario 2 for the year 2023) to £11.437 million (as indicated in Scenario 2 for the year 2027). This denotes an average increment of approximately £0.5 million per year during the period from 2023 to 2027, with the largest allocation being consumed by the group of children from the second-most-deprived background.

4. Discussion

This study fills a gap within the current literature by providing a solution to effectively address global health disparities within countries by focusing on the hospital level and the delivery of services at a community level. Existing studies tend to adopt a 'one size fits all' approach, relying on economic and mathematical modelling. The major drawback of these approaches is their population-level assumptions, which overlook the individual needs of patients and the broader system context of health inequalities. SimulEQUITY addresses this significant gap by providing a holistic simulation-based modelling framework that is versatile and capable of being implemented within different healthcare contexts. It seeks to optimize resources, evaluate the impact of interventions, and include a forecasting dimension in one platform. The implication is that any healthcare organisation can tailor the model to its local needs, which could have a greater impact if it connected a series of healthcare organisations in a region to deliver services according to regional or national healthcare strategies. The potential is to not only assist in local healthcare delivery to reduce inequalities but also to connect providers together at different geographical scales of analysis.

SimulEQUITY, as an easy-to-use decision-support toolkit, offers a practical avenue for mitigating health inequality depending on how it connects with health care policy. The model has wider global applications, in settings where appropriate data exists, to target resources to address inequality, especially in the developed world, although also in the Global South contexts where data exists. However, this will have a number of contingent factors that could impact its implementation such as the willingness of hospital managers to embrace change and allocate time and resources to this activity. Other operational barriers, such as resistance to change existing practices, may affect stakeholder engagement along with the obvious initial training needs to operate the model. There are also unintended consequences from the model such as its potential to simulate different socio-economic distributions to explore and interrogate cross-sectional measures of inequality.

One of the key elements in cascading the model's transformative power in hospital planning will be in the communication process to the practitioner audience. Fig. 8 summarises the value of the model that will need to be part of a multi-stage campaign by the research team, stakeholders, and policymakers to highlight how decision-making may be enhanced. Recommendation and evidence of the benefit from implementation at pilot hospitals that adopt the model will be critical in breaking down barriers to the wider dissemination of the benefits for professional practice in tackling inequality.

At an operational level, SimulEQUITY has seamless adaptability for

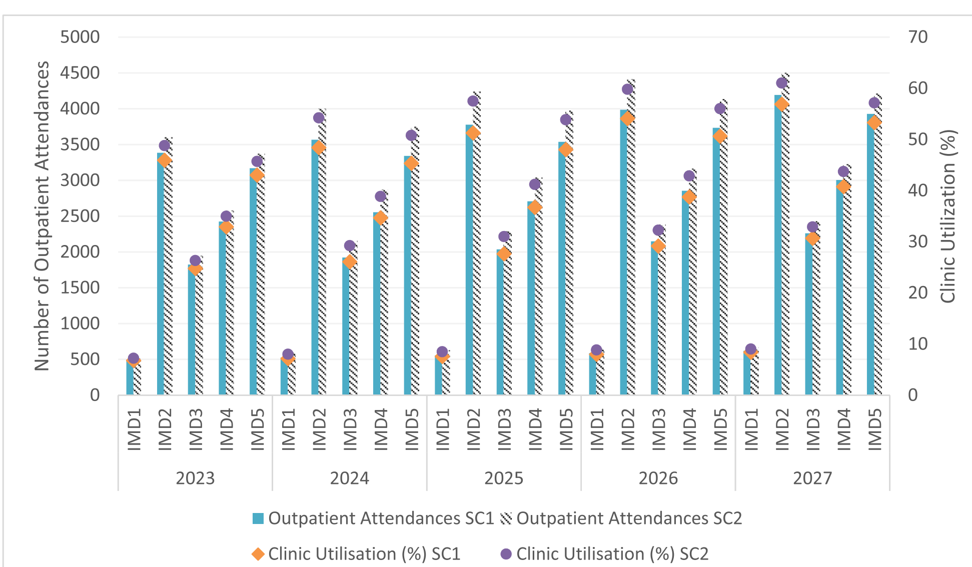

Fig. 6. Outpatient attendances and the impact on clinic utilization for the paediatric specialty broken down by IMDs, comparing the two scenarios for the period 2023–2027. SC1: Scenario 1; SC2: Scenario 2; IMD: Index of multiple deprivation.

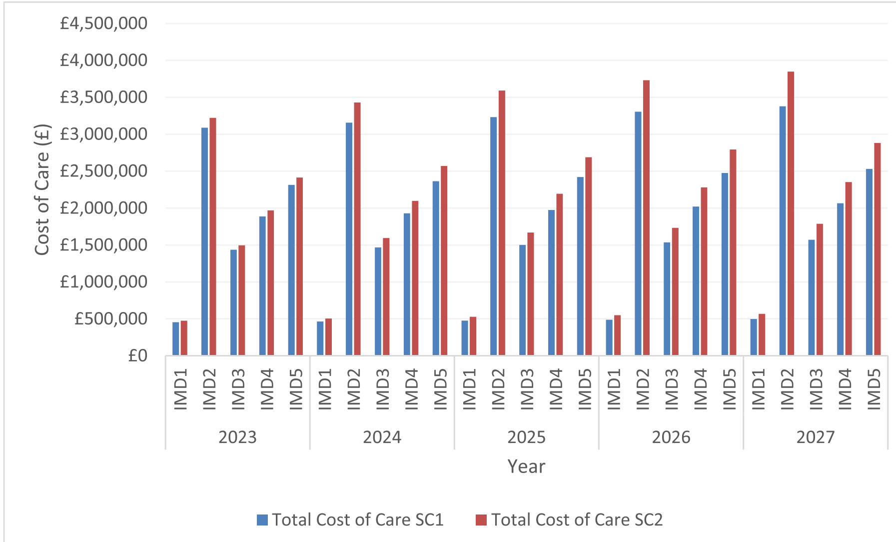

Fig. 7. Total cost of care for the paediatrics specialty broken down by IMDs, comparing the two scenarios for the period 2023–2027. SC1: Scenario 1; SC2: Scenario 2; IMD: Index of multiple deprivation.

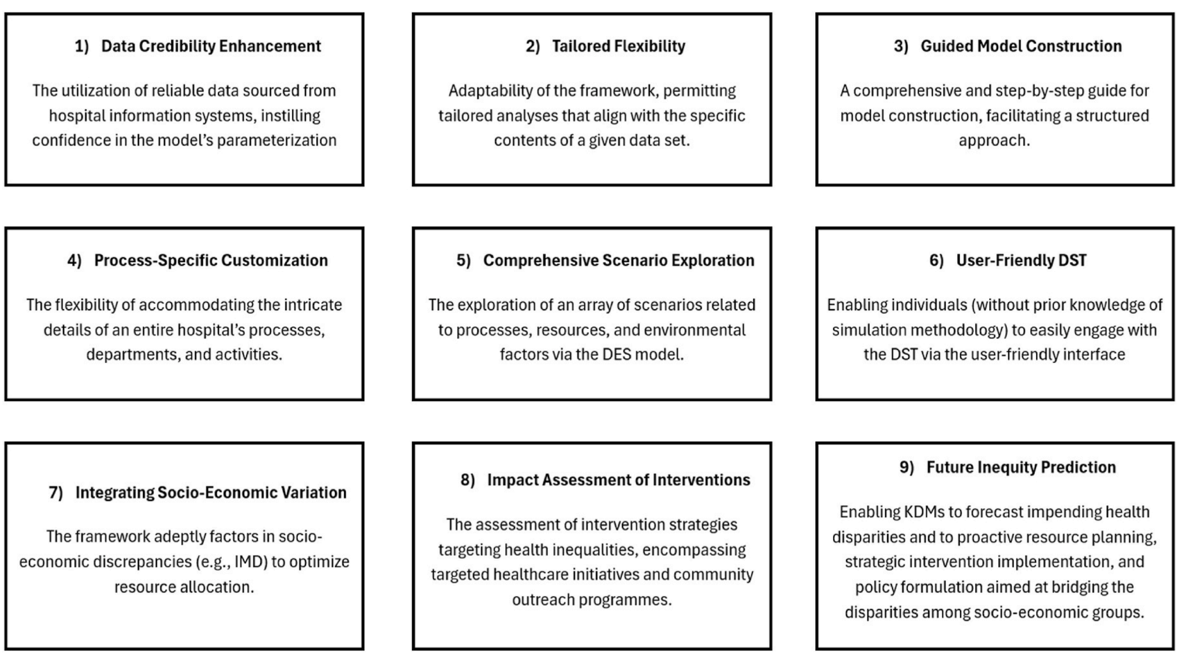

Fig. 8. The benefits of SimulEQUITY. DES: Discrete-event simulation, DST: decision-support tool, IMD: index of multiple deprivation, KDM: key decision-maker.

model updates, achieved through re-estimation of the parameters using new data; this is advantageous when complex systems, like hospitals, undergo abrupt shocks (e.g., the COVID-19 pandemic), including those influenced by external factors, such as policy changes, economic shifts, and public health trends.

To support the implementation of SimulEQUITY, two training sessions were conducted post-completion of the simulation model. These sessions were designed to familiarize the end-users with the functionalities of SimulEQUITY, ensuring they were adept at navigating and interpreting the outputs generated by the tool. The objective was to empower decision-makers with the necessary skills and insights to effectively use SimulEQUITY in their decision-making processes. Throughout the implementation process, our team provided ongoing support at each stage, addressing any queries or concerns raised by end-users. This support was crucial in ensuring a seamless integration of the tool into existing hospital decision-making processes.

Limitations arose in our study as the SimulEQUITY framework was tailored to a 'conventional' hospital model. Adjustments are needed for application to alternative care models, requiring proficiency in mathematics, programming, and statistical analysis. Nevertheless, applying SimulEQUITY to the case of an NHS hospital in England demonstrates its potential role in strategic planning and day-to-day decision-making. The holistic and system interconnections which the model allows to be captured start to address the notion that addressing health disparities are an insurmountable 'wicked problem' at a local scale. The model enables managers to link service demand, resource utilization, and operational needs together for the entire hospital. The scenario-planning options in the model are rooted in local community needs and enable individual hospitals to forecast operational needs to 2027 in terms of addressing health inequalities. As part of a co-created activity with hospital managers, we were able to establish the robustness of a 'Baseline Scenario', in which existing services are maintained as they are, and an 'Increased Outpatient Attendances and Elective Admissions' scenario, to progressively address backlogs. These backlogs are a major public policy concern within the UK healthcare system post-COVID with 7.61 million cases (comprising 6.39 million individual cases) on waiting lists, so healthcare managers are looking for options to cut these lists. Our research demonstrated how the model's use in the paediatric medical specialism could assist with reducing waiting times and its budgetary implications. In other words, SimulEQUITY's practical application to healthcare decision-making illustrates its efficacy in addressing SES disparities through proactive resource planning. The patient flow in real-world settings is inherently more intricate, involving unpredictable movements of patients. Users should anticipate that the model, based on a generic flow, may produce outputs that differ ever so slightly from the real world. It is important to note, however, that these differences are minor and would not mislead decision-makers.

Our future research will focus on seamlessly integrating SimulEQUITY with existing electronic medical record systems to increase the efficiency of updating the model. We will also be pursuing wider dissemination of the model in the NHS by illustrating the value of the SimulEQUITY framework. We are committed to closely collaborating with hospitals to support its implementation as a strategic tool to help manage change and foster design-oriented thinking. This will require staff training to make sure support from senior management is available at the point of need within the hospital setting.

In summary, the paper demonstrates the practical application of systems thinking as a holistic and synthesizing approach that is suited to solving complex health management problems and shows that they are not insurmountable, and that allows specialized targeted healthcare programmes, community outreach initiatives, preventive measures, and policy changes to be integrated. The wider adoption of the model in other healthcare settings globally may offer an attractive option as a prudent way forward that does not involve major financial risks in implementing an untried and untested model that can be tailored to local needs.

Ethics approval

No ethics approval was required for this project as it did not involve human subjects, or any sensitive patient information that would necessitate ethical oversight.

Declaration of interest

None.

CRediT authorship contribution statement

Eren Demir: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Usame Yakutcan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Stephen Page:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2024.116786.

Appendix 1

A. Part III: Model Development

Step 6. **Model Translation:** The model is **translated** into the conceptual **model** with input settings within a computer simulation environment. The simulation can be developed via a programming language or commercial software (e.g., Simul8).

Step 7. **Validation and Verification:** The conceptual model is **validated** to establish that the hospital setting is represented as accurately as possible. If there are any discrepancies, go back to Step 2. The simulation is also **validated** by comparing model outputs with actual data from the healthcare setting. **Verification** of the simulation **model** that was developed is undertaken to ascertain whether the patient flow and inputs (percentages and times) are represented accurately. If there are any inconsistencies, go back to Step 6 and refine the model as necessary.

Step 8. **Experimentation:** The **experiment(s)** are then designed by considering the problem (i.e., health inequality) and objectives as identified in Step 1. For example, providing after-hours services, home visits, or transportation.

SimulEQUITY can be used to better understand the impact of interventions that could potentially reduce health inequity. Sample scenarios can be embedded in the tool to combat social disparities, such as changes in demand-capacity and free transportation service to attend appointments. Users have the option to either use pre-set scenarios or create custom scenarios/interventions tailored to their specific issues. The model's output provides valuable insights, empowering key decision-makers to make informed choices ahead of real-world implementations.

Step 9. **Model Run and Analysis: The completed model is run** and the **analysis of** model outputs is thoroughly checked, especially focusing on the results on SI and health inequality.

Step 10. **Reporting and Recommendation:** At this stage**,** a **report** is produced explaining the problem, objective, scenarios (experiments), and analysis of results. The report concludes by providing **recommendations** to alleviate health inequalities as well as outlining strategies for effective implementation.

B. Verification and Validation of SimulEQUITY

The model was checked for accuracy and reliability to ensure it worked for different scenarios *(Step 7)*. The development of the model follows a meticulous step-by-step approach, with a rigorous cross-checking of both input data and produced outputs at each stage. Following the identification of the most appropriate distribution, a rigorous testing and validation phase ensues within the simulation model. This phase is executed through a trial-and-error methodology, assessing the performance of the selected distribution against real-world data. The iterative process ensures that the simulated data aligns closely with the actual data, enhancing the model's accuracy and reliability. This comprehensive approach to parameter estimation and validation is critical in maintaining the fidelity and effectiveness of the simulation model.

Moreover, the model's logic and routings undergo thorough testing to ensure their proper functionality. Throughout the development process, we conduct intensive tests to identify any instances of irrelevant inputs or outputs. In such cases, the related components are scrutinized in detail to pinpoint and resolve the issues. This comprehensive validation process involves a careful examination of all facets of the model, both during the developmental phase and in the post-development stage. This meticulous approach is aimed at ensuring the accuracy, reliability, and robustness of the model, addressing any discrepancies or anomalies that may arise during its construction and subsequent testing.

To check the model's outputs, we used black-box validation (Law, 2007), which is a popular technique used for this purpose. The following parameters were chosen for validation, number of required beds, waiting time, amount of activity in each department, and clinic utilizations broken down by IMDs. The results were very close to the real data (i.e., differing by less than 5%) showing that the simulation model is accurate.

To make sure our validation was robust, white-box validation (Law, 2007) was utilized to further test each component of the model for consistency as captured in the pathway. We did this by looking at all the different parts of the model during both the development and post-development phases.

Furthermore, face validity was employed to ascertain the model's alignment with the perspectives of key stakeholders, such as consultants and nurses. This involved running each phase of the simulation and receiving affirmation from these stakeholders regarding the model's accurate depiction of the hospital. This meticulous and all-encompassing validation procedure reinforced the model's accuracy and reliability before it was endorsed for use in practice.

Appendix 2

Table A1
The input parameters associated with the paediatrics specialty

Parameter	Estimate	Distribution	Resource
Demand			
Activity for Financial Year 2022/23			
Inpatient Service			
Electives	444	Fixed	HD
Non-electives	4961	Fixed	HD
Outpatient Service			
First and Follow-Up Attendances	12,095	Fixed	HD
Did Not Attends	595	Fixed	HD
Cancellations	1,756	Fixed	HD
Forecasted Activity for Inpatient Admissions, Outpatient Attendances, and ED	Forecasted	Fixed	HD
Staff			
No. of Consultants	9	Fixed	HD
No. of Other Doctors	28	Fixed	HD
No. of Other Support Staff	0	Fixed	HD
No. of Nurses	75	Fixed	HD
Percentage of a Consultant's Time Spent in Outpatient Services	42	Fixed	HD
Percentage of Other Doctor's Time Spent in Outpatient Services	42	Fixed	HD
Percentage of Other Staff's Time Spent in Outpatient services	0	Fixed	HD
Percentage of Nurse's Time Spent in Outpatient Services	2	Fixed	HD
The Recommended Nurse-to-Bed Ratio	0.8	Fixed	HD
Bed and Clinic Capacity			
Bed Capacity for Elective Admissions	15	Fixed	HD
Bed Capacity for Non-elective Admissions	16	Fixed	HD
Annual Clinic Slot Capacity	7,373	Fixed	HD
Recommended Bed Occupancy Level	0.85	Fixed	HD
Waiting Time			
Mean Wait Time (in Days) for Elective Admission (in Days)	126	Log-Normal	HD
Mean Wait Time (in Days) for First Outpatient Appointment	54	Log-Normal	HD
Mean No. of Follow-Ups	0.96	Poisson	HD
Theatre Utilization^	N/A	N/A	N/A
Revenue			
Elective Admission	£1,723	Average	NHS England*
Non-elective Admission	£1,186	Average	NHS England*
First Outpatient Attendance	£242	Fixed	NHS England*
Follow-Up Outpatient Attendance	£163	Fixed	NHS England*
Mean Cost for Diagnostic Procedures	£69	Average	NHS England*
Mean Cost for Treatment Procedures	£174	Average	NHS England*
Index of Multiple Deprivation			
Outpatient Attendances			
First Attendances			
1 (Most Deprived)	4.27%	Multinomial	HES
2	30.83%	Multinomial	HES
3	15.45%	Multinomial	HES
4	21.80%	Multinomial	HES
5 (Least Deprived)	27.65%	Multinomial	HES
Follow-Up Attendances			
1	4.56%	Multinomial	HES
2	29.06%	Multinomial	HES

(*continued on next page*)

Table A1 (*continued*)

Parameter	Estimate	Distribution	Resource
3	16.83%	Multinomial	HES
4	21.11%	Multinomial	HES
5	28.44%	Multinomial	HES
Inpatient Admissions			
Electives			
1 (Most Deprived)	5.75%	Multinomial	HES
2	40.26%	Multinomial	HES
3	12.62%	Multinomial	HES
4	20.41%	Multinomial	HES
5 (Least Deprived)	20.96%	Multinomial	HES
Non-Electives			
1	5.21%	Multinomial	HES
2	34.47%	Multinomial	HES
3	17.62%	Multinomial	HES
4	18.94%	Multinomial	HES
5	23.77%	Multinomial	HES
Length of Stay (Days)			
Electives			
1 (Most Deprived)	2.6	Log-Normal	HES
2	2.4	Log-Normal	HES
3	2.9	Log-Normal	HES
4	2.7	Log-Normal	HES
5 (Least Deprived)	2.4	Log-Normal	HES
Non-electives			
1	4.0	Log-Normal	HES
2	3.3	Log-Normal	HES
3	3.1	Log-Normal	HES
4	2.8	Log-Normal	HES
5	3.1	Log-Normal	HES
Patient Characteristics & Routing			
Sex	See Tables S1 and S2 in the supplementary file	Multinomial	HES
Age Group		Multinomial	HES
Ethnicity		Multinomial	HES
Attendance		Multinomial	HES
Discharge Method		Multinomial	HES

Abbreviations: LoS: Length of Stay; HD: Hospital Data; HES: Hospital Episodes Statistics; HRG: Healthcare Resource Groups; N/A: not applicable; NHS: National Health Service; ^: Theatre Utilization is a model input as well, but it is not applicable to the paediatrics specialty, hence the estimates are given as N/A. *: National Tariff Payment System (2022–23).

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