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Optimising patient flow dynamics at a south African public hospital with resource constraints

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Abstract

In this paper, an application of a System Dynamics (SD) model is presented, which explores the stages of patient flow processes. The model presented represents a participatory methodological framework for healthcare simulation studies, capable of tackling design challenges that emerge at various stages of the modelling and simulation process, ultimately leading to enhanced context-specific solutions. It is hoped this was achieved by highlighting the potential utilisation of SD simulation to generate a patient flow perspective of healthcare and developing dialogue, which enhanced the division of resource allocation surrounding the various stages of the patient flow processes. Challenges were analysed using SD archetypes and leverage points for intervention facilitated by PAR (Participatory Action Research) Reflection Points. Using SD archetypes can potentially aid hospital managers in recognising existing patterns of behaviour within the organisation. These archetypes provided valuable insights into the underlying system structures that produce such behavioural patterns. Through the application of system archetypes in the critical analysis of healthcare challenges, loopholes in management's strategic planning processes were identified. Furthermore, the study demonstrated the potential to challenge and overcome shortcomings in the hospital system by adapting future policy implementation, as evidenced by results from the modelling outcomes. Managerial structures may consider modifying policies to avoid potential pitfalls and prevent costly learning experiences by utilising data generated from the 'what-if-scenario' generated by the SD model.

Keywords: Participatory action research, Public healthcare, System dynamics.

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1. Introduction and Problem Context

This objective was linked to the assessment of establishing a pragmatic application of an SD model in a healthcare context, thereby eliciting suggestions for improving patient care quality by optimising patient flow factors. The literature abounds with studies demonstrating how SD models display the potential to unlock high-leverage interventions that help ameliorate existing imbalances in the system [1-4]. SD approaches modelling and other systems thinking modalities have garnered widespread academic attention, especially in healthcare [5-8].

Healthcare resource allocation can be contextualised within a broader framework whilst utilising SD-based heuristics to explore the risk-free testing of alternative interventions [2]. It has been established by Hankey [9] that it is essential for healthcare systems to initially study patient flow methods, which seek to identify bottlenecks in the system, following which methods can be introduced to address these factors. The present research proposes to develop a tool based on an SD model to understand the modalities pertaining to the feedback mechanisms among the ED and elective patients awaiting bed occupancy in the Orthopaedic wards.

A hybrid approach was generated using stock-flow symbols and CLDs (Causal Loop Diagrams) from the SD armamentarium of tools. Data from interviews, ethnographic sources and quantitative data revealed patterns that enabled the development of stock-flow maps and CLDs. This lent support to this paper's aims and objectives, which aimed to study competing patient flows and create efficacy within the system [10-12]. It is hoped that generating an SD model can be utilised which addresses overcrowding in the ED by a dearth of beds available in the wards without compromising on contributing to the long list of elective patient surges. Optimal management of patient flow through the system is well established as a significant contributor to improving the quality of healthcare services [6, 8, 13]. This can be primarily achieved by demonstrating how potential risk-free experimentation and interactive policy formulation can be utilised to reconfigure healthcare delivery using models that evaluate patient flow [14, 15].

Emergency Department (ED) overcrowding with long waiting periods for elective surgery are two of the most often cited issues in public health systems [16]. The situation at Addington Hospital has been regularly reported in the newspapers [17]. These articles in the media give an impression that health resources are not well aligned and are out of sync with the hospitalization care needs of patients. This creates tension and disorders within the system between elective patients and those who are admitted acutely to the ED. Elective patients often wait longer in anticipation of a bed due to unpredictable new arrivals from the ED, which block bed availability in the ward.

By utilising a combination of SD tools, it is hoped that insights can be generated to aid policy developers in implementing crucial decisions to keep the system operating at optimal flow levels. During the peak holiday season, the dire need for hospital beds exceeds capacity in the short term, and spikes in demand occur. This can mainly be attributed to a direct rise in emergency department admissions to the hospital [18]. The scenario above gives rise to heightened waiting lists for elective surgeries, prioritising accident and emergency patients, resulting in extended hospital stays and consequently diminished patient rates of discharge. This paper hopes to underscore the necessity of enhancing patient throughput by, among other measures, establishing a structured discharge process designed to promote patient-centered care and ensure continuity of care. The significance of effective patient flow dynamics has grown markedly in the post-COVID-19 era. The pandemic has highlighted systemic vulnerabilities within healthcare systems, underscoring the critical importance of optimizing service delivery efficiency and streamlining patient transitions across care platforms [19]. Such measures are essential to mitigate patient dissatisfaction, minimize medico-legal risks, and safeguard the well-being of healthcare staff.

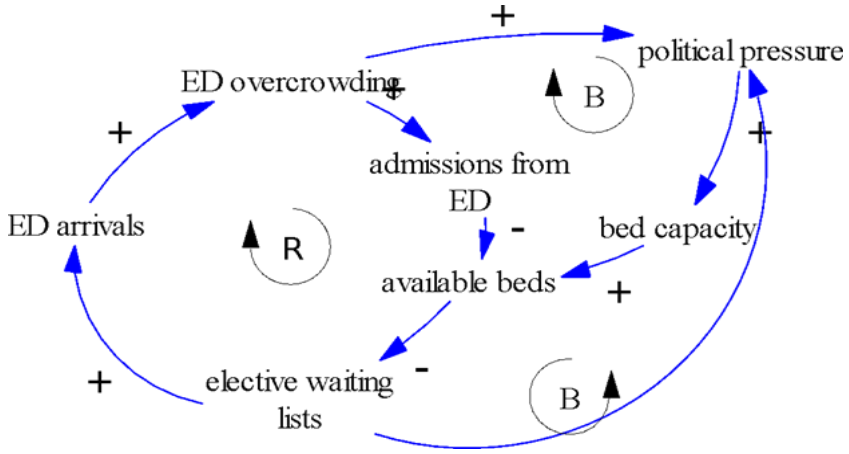

Figure 1.
CLD demonstrating interacting ED and in-patient ward dynamics.

The CLD in Figure 1 illustrates the challenges associated with maximal admission to the ED at Addington Hospital, affecting ward admission. It explicitly outlines the hindrances in the elective admission flow precipitated by the increase in the patients in the ED.

The researcher acknowledges that the CLD in Figure1 remains simplistic and reductive in describing the hospital system's rigour to encounter demand variations. It addresses this via feedback loops introduced in the CLD explaining the mechanisms activated to balance the erratic demand. Moreover, the model can test the effects of backup routes of care, which are directed towards maintaining equilibrium if unpredictable rises in ED admissions occur.

In Figure 1, the feedback loop labelled (R) exhibits the realities of ED overflows affecting the incremental increase of patients to the Orthopaedic wards. This is based on an a priori recognition that not all the patients evaluated in the ED get admitted. The core utility of the model lies in its value to describe at a glance at what stakes this balance is obtained (i.e. awareness of dissatisfaction, which in turn triggers the ‘political pressure’ of the CLD depicted in Figure 1.)

Crucially, when ED congestion becomes chronic, awareness of patient dissatisfaction and delays triggers political pressure, which in this context includes direct managerial interventions, reallocation of ward resources, expedited discharges, or policy mandates aimed at reducing ED crowding. Such top-down directives may include orders to “make space,” fast-track certain cases, or expand admission quotas; all of which increase the inflow into the Orthopaedic ward, reinforcing systemic strain.

This reinforcing loop thus highlights the unintended consequences of reactive strategies in managing overflow; where solving the problem in one part of the system risks exacerbating it in another.

A more significant influx of patients to be admitted from the ED precipitates a reduction of the beds available in the Orthopaedic wards, with a corresponding significant blockage of elective patient admissions. The result is high bed occupancies, leaving less bed capacity available to accommodate planned elective admissions. This contributes significantly towards increasing the elective waiting lists. In some instances, patients go directly to complain to the hospital Public Relations Officer, who in turn applies pressure on the ward doctors to avoid negative publicity in the media. Thus, a reinforcing loop becomes extant. The upstream factors of ‘political pressure’ affect both the ED maximal occupancy rates and the prolonged elective waiting periods. These adverse circumstances receive media coverage, triggering politicians and managerial constructs to act. The researcher has been aware of the institution's ‘shadow sides’ [15, 20, 21] related to organisational politics. The CLD in Figure 1 demonstrates how exogenous variables in the form of political duress can give rise to negative feedback, which affects the system by creating balancing loops.

One possible approach is to reduce the number of patients referred to the ED without a relevant Orthopaedic surgical pathology. Another is levelled at ward-level intervention by discharging patients in shorter time frames to increase admissions during peak periods [19, 22-24].

Data gleaned from the interview guide; attached as a supplementary file, with Orthopaedic Staff members in the ED highlighted issues pertaining to patients waiting long hours on stretchers awaiting a bed in the Orthopaedic ward. As part of the participatory modelling process, qualitative data were gathered through semi-structured interviews with a purposive sample of key hospital stakeholders, including senior managers, ward doctors, nursing staff, and allied health professionals from the Orthopaedic Department and Emergency Department at Addington Hospital. These participants were selected based on their direct involvement in patient flow decisions and frontline experience with bed management. The interview guide, developed specifically for this study - explored themes such as perceived bottlenecks in patient flow, admission and discharge practices, interdepartmental coordination, challenges with elective versus emergency case prioritisation, and the feasibility of proposed interventions. Insights derived from these interviews were used to inform the development of causal loop diagrams, identify key variables in the stock-flow models, and shape the formulation of PAR Reflection Points throughout the study.

This emphasises the second approach of developing interventions to augment the ease of intra- hospital patient flow from the ED to the inpatient ward. Proposed ways of establishing this are derived from literature suggesting accelerating discharge times [16, 24-26]. The researcher was cognisant of studies which raise alarm bells against premature discharge times, which may result in unforeseen adverse effects of re- admission associated with complications; hence, the action would seem counterintuitive and detrimental to overall patient flow management [27-29].

To overcome overcrowding in the ED, circumstances exploring increasing hospital bed capacity need to be explored. The effects of altering bed capacity as a variable have long been studied in the literature [2, 13, 30-32]. Some authors have recommended this route as a variable to be adjusted to solve the challenges of incremental ED admissions vs. creating space for elective patients requiring surgery. This sentiment has also been echoed by several staff members at Addington Hospital who were interviewed during the data collection processes and suggested that increasing bed capacity as a variable should be considered. They proposed that this can be achieved by hiring more nursing staff such that wards which have been closed can be reopened to accommodate more patients. This pressure could potentially be alleviated using a corresponding bed capacity increase, which appeared to be the principal obstruction of the system. Without such an increase (in Figure 1, activated by the political pressure loop), the system can be restored to equilibrium by restricting the flow of elective admissions.

In this paper, due consideration is given to the rise of the ward bed capacity, which can be perceived as a significant, vulnerable, fragile system point [16]. The researcher thus set out to ascertain if this route is viable and pragmatic as a proposed solution specific to the settings of the Orthopaedic Department at Addington Hospital. The study also investigated the unintended consequences of well-intended direct interventions as per SD paradigms [29].

The model generated employs a participatory strategy facilitated by increased stakeholder involvement, which enhances a shared comprehension of modelling, the exchange of knowledge,

and the formulation of policies [8, 33]. Utilising modelling rooted in local and contextual knowledge has the potential to navigate knowledge disputes from the perspective of social learning. It reduces the likelihood of distorting stakeholders' objectives and principles [34]. The consensus is vital in the literature that successful stakeholder engagement profoundly impacts the results of a modelling study within a social organisation, thereby increasing the likelihood of endorsing and executing the model's outcomes [12, 35]. The manuscript introduces a series of *PAR Reflection Points* — structured syntheses of key insights, dilemmas, and decisions that emerged from iterative participatory cycles with hospital stakeholders. These points serve to anchor the evolving narrative, highlighting moments of collective learning and guiding adaptive action within the research process.

Table 1.
PAR reflection point 1.

PAR Reflection Points
Bed capacity limitations
After lengthy discussions with senior managerial staff at Addington Hospital as part of the PAR methodological cycle, the researcher has concluded that augmenting bed capacity is not a viable option and has thus become a limiting factor due to shortages in nursing staff. Hence, simulating a model around bed capacity increase will not be realistic, as demonstrated in other studies [8, 30-32]. Based on real-world settings at Addington Hospital, this necessitated a rerouting of approaches to consider alternate interventions. After overcoming the initial setback of not increasing bed capacity as an option, the researcher interestingly came across other studies which have circumvented this shortcoming. They have demonstrated that the provision of additional hospital beds does not establish as significant of an impact on the total number of patients waiting as that of implementing other options, such as intermediate care policies. These studies have revealed that considering patients in the various stages of care can significantly reduce waiting times rather than simply increasing bed capacity as a variable [25, 31, 32]. There was a more considerable impact on the total number of patients waiting for a bed, resulting from alterations to intermediate care and length of stay reductions rather than hospital bed capacities. This phenomenon is congruent with stock-flow models [10] best explained by the different variables associated with those policies. The former involves changes to 'rate' variables and the latter to 'stock' variables.
A stock is an expression for continuous entities that accumulate or lessen over time, whilst a flow variable denotes the rate of change in a stock [10]. Figure 2 [10] illustrates the stock- flow model for hospital admissions. There are two clouds consisting of 'source' and 'sink'. The patients are referred to as the entities flowing through the system. The rectangle illustrates a stock or level of patients occupying beds. The arrows denote admissions and discharge, and the valves exhibit the flow rate. Systems can have properties which represent 'auxiliary' or 'soft' variables that may not directly influence the system but still impact overall behaviour. The model can be parameterised and quickly developed with SD software programs [2]. When additional beds are procured, more patients render the wards full.
However, the effect is short-lived. As soon as the new bed capacity is reached, the number of patients in the hospital stabilises, and the elective admission waiting list is inflated [13]. This is a phenomenon best explained by the notion that increasing bed capacity is a 'stock' increase policy, which will have a once-off and time-limited impact on the pre-hospital waiting list. There is also an associated risk that this intervention will stimulate demand for further hospital care requirements [15, 29].
PAR Reflection Points
Expenditure

For systems thinking to gain widespread awareness and seamlessly merge into the public health domain, various practical obstacles must be identified and addressed [15, 36, 37]. It has been suggested that, at times, the complexity and depth of systems thinking may be dismissed as being far too complex [2, 36].

For systems thinking to pragmatically and successfully emerge as a guiding paradigm in the context of South African resource-poor state-funded hospitals such as Addington Hospital, there needs to be a considered, practical and accessible approach. Applying SD in practice in low- to middle-income countries has a long- standing history of vastly overlooking SD as a robust modality of addressing public healthcare challenges [38]. Towards this end, the researcher has welcomed utilitarian options grounded in driving down fiscal costs and engaging with a user-friendly interface familiar to staff in public healthcare contexts. Several authors have commented that simulation software expenses are not economically viable for hospital settings with meagre resources. SD Modelling, which relies on statistical expertise, is associated with considerable financial strain on the system [2, 39, 40]. While hospital informatics systems compile data in various forms, the data is rarely presented in high-quality data-capturing methods; hence, external statistical guidance is sought, further contributing to incremental expenditure.

Subsequently, the researcher has demonstrated how institutions can bypass excessive financial costs by utilising the ubiquitous and easily accessible Excel Spreadsheet or by downloading free software programs. The theoretical expressions generated in this paper used a free downloadable software program called Matlab.

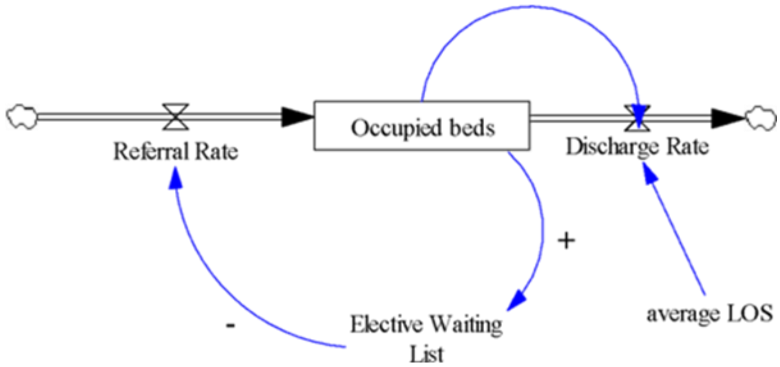

Figure 2.
Stock-flow model for hospital admissions adapted from Brailsford.
Source: Brailsford [10].

2. Methods: Queuing Network Modelling to Analyse Orthopaedic Patient Flow

In this paper, the modelling framework selected to study optimal patient flow is based on queuing network models. Queuing theory is founded on a mathematical model generated to predict queue lengths and waiting times [9, 41]. Normative applications of queuing models have been prevalent in communication systems whereby a network consists of many single-server nodes. A parameter typically defines the characteristic of a node: the service rate, i.e. the number of requests singular servers at that node can process within a given unit of time. In an uncomplicated queue, a constant service rate concerning service time follows an exponential distribution [9, 41-43].

It was essential for the researcher to become familiarised and more adept with the queuing network model since it is cited in the literature as a modality to be considered in healthcare. Previously studied parameters include the enhancement of operational running in areas of waiting times, efficacious use of beds and overall bolstering of healthcare system design [44-46].

2.1. Reasons for Selecting the Queuing Network Model

2.1.1. Ease of Model Usage

The researcher is relatively inexperienced in SD modelling. The literature asserts that queuing models are more accessible than other models since they require less data and generate more generic outcomes than other patient flow methods [9, 44]. Patient flow modelling is based foundationally on simple mathematical equations, relying on a queuing model at its most basic level comprising four levels: arrivals, servers, service principles, and ultimately giving insights related to patient flow in the system [45-47].

2.1.2. Utility And Versatility of the Model

The precipices above speak to the objective of this paper, which seeks to employ an SD model for transformation which will assist in reducing the number of patients waiting for prolonged periods before receiving treatment. This is validated by Cochran and Roche [47] who asserts that this method has successfully been tried and tested in generating guidelines for how multiple system variables can be processed via a single computational model. The researcher views the utilitarian value of this model as a further manner by which healthcare managers can be engaged to effect change.

Healthcare quality indicators can be achieved by visualising queuing patterns in real-time by being able to view waiting times and transfer probabilities. It is also quite an attractive feature of queuing theory, which enhances data collection by integrating mathematical equations with existing data collection methods. The modelling framework enables a more comprehensive means of data collation for hospitals, which has the added advantage of being economically feasible. Healthcare providers and managers can extend potential planning opportunities using a more robust, scientifically supported method [9, 48].

2.1.3. Addressing Limitations of Other Studies

Most of the studies centred around SD modelling place emphasis on deducing steady-state solutions, specifically, the system's behaviour at equilibrium after it has been in operation for an extended period for systems without bed shortages [49]. Considering the specific settings of Addington Hospital, including bed capacity constraints, will yield a more realistic scenario of the clinical conditions in the Orthopaedic Surgical wards. Hence, queuing models address the limitations of the previous studies mentioned above, i.e., no restriction on bed numbers. The researcher aims to demonstrate an SD model in a hospital with bed capacity restrictions to present a pragmatic tool for upstream policy developers [9, 19, 42].

2.2. Application of the Queuing Model

Within healthcare parameters, patients can be seen as traversing through several phases of care that can be classified according to the patient's needs. These include the initial assessment and diagnosis, followed by acute treatment, rehabilitation, and sometimes extending into long-stay care [9, 50]. Considering bed constraints at Addington Hospital, this compartmental modelling approach has been quite a breakthrough in managing bed occupancy factors. Other papers have demonstrated how occupancy rates can be divided into similar phases, which merge the nexus of influencing the admission and discharge of patients [42, 51].

The researcher has divided patients in the Orthopaedic Ward into the following conceptual phases on which the model is based.

2.2.1. Stage One

Upon admission, patients enter into the first stage, which corresponds to their assessment and diagnosis, conferring them with a pre-operative status.

The average LOS for this stage is 11 days

2.2.2. Stage Two

These patients are now deemed to be post-operative and undergo some form of rehabilitation by the allied health discipline team, i.e. physiotherapy. From this stage, patients get discharged home either directly or by way of a step-down facility. If complications arise during this stage, they enter the next stage.

The average LOS for this stage is 14 days

2.2.3. Stage Three

Patients in this stage are considered to be in long-stay care, usually due to factors arising from complications during surgery or being unable to be discharged home, requiring social worker intervention, i.e. the patient has no fixed abode and requires placement or delays in seeking out appropriate step-down facilities.

The average LOS in this stage is approximately 21 days.

Eventually, all patients are discharged. Transfer probabilities between each stage have been worked out utilising mathematical equations derived from similar closed queuing network papers [9, 42, 52]. These equations are displayed in (Appendix A). Equations numbered 1,5,6,7,8 were considered relevant for this model [42].

The researcher values the feature in the mathematical model, which notably includes a bed capacity limitation K., i.e. there are a total number of K beds that can be potentially occupied in the ward and is executed on a pre-existing condition that the system operates at maximal capacity [9, 42]. This notion is entirely congruent with prevailing conditions at Addington Hospital, whereby bed occupancy rates are always at their maximum rate. Hence, waiting lists for elective surgery are at total capacity. Incorporating clinical personnel as an additional resource set would have yielded a more intricate model; however, this may have introduced complications that might have undermined the precision of the model due to the fluctuations within staff scheduling systems over varying time frames such as days, weeks, or months [24].

At each stage of care, a discharge is immediately replaced by a new admission, necessitating admission to the first stage. Systems which operate within these parameters are known as closed systems [9]. This assumption of immediate replacement is a simplifying assumption made for the purposes of modelling clarity and computational feasibility. While it does not fully capture real-world delays in bed turnover; such as cleaning, administrative processing, or variability in patient arrival—it enables a steady-state analysis of patient flow dynamics, focusing on structural bottlenecks rather than transient fluctuations.

This facilitates a model permitting patient flow through the ward with 'M phases' based on a closed queuing network with 'M nodes' each representing a stage of patient care, i.e. stage one, two or three, as explained above [42].

The term node is a derivative from the queuing network model whereby a service node is represented by one of the patient care stages. Service time follows an exponential distribution with the mean being (μ) where (μ) represents the uninterrupted service rate per bed, i.e. the mean number of patients receiving care per unit of time per bed. The unit times are taken to denote days throughout the model. The number of 'servers' refers to occupied patient beds [42]. This model focuses on the allocation of patients amongst the different stages (e.g. the number of beds occupied by patients in stage three, which is deemed an extended stay). Credence is also given to the effective admission and discharge rates of the overall system.

For example, in a thirty-bed hospital ward, a healthcare practitioner may come across patients occupying ten beds categorised under stage one (pre-operative), twelve in stage two (post- operative) and the remaining eight in stage three (long-stay). Hence, during the ward round, the three-tiered queuing network model will comprise ten servers at node one, twelve at node two and eight at node three. These figures will fluctuate depending on the specific Orthopaedic care needs of the patients as they move between the various treatment stages.

Therefore, in this paper, the model is established upon a defined number of service nodes, i.e. stages of care, whilst allowing for a variable number of servers, i.e. hospital beds. This approach is consistent with a queuing network model, which has a built-in heuristic incorporating a capacity constraint on the system [9, 42, 43], i.e. the total number of fixed beds in the Orthopaedic wards setting.

A further advantage of this model is the permutation of varying model inputs, such as the average length of stay in the various stages, and establishing the transfer probabilities between the stages. In lieu of these measures, it is hoped that a steady-state solution can be obtained which will generate performance indicators of the flow of patients and evaluate the long-term challenges of corresponding policy alterations. This will be instrumental in future planning and introducing control measures to enhance patient flow [19]. The application of queueing networks in modeling material handling systems across various intralogistics domains has proven instrumental in enabling researchers and industry professionals to examine and analyse complex system topologies and behaviors. Furthermore, the integration of queueing networks with numerical methods and techniques has unequivocally contributed to the enhancement and optimisation of these systems [43].

2.3. System Performance Indicators

The researcher calculated the critical measures of this system using Equation 1 [42]. From the perspective of ward patients occupying beds at the various stages, the proportional arrival rate at each stage is determined using Equation 1 (Appendix A).

Hence, on average, 39.23 % of the 51 allocated Orthopaedic beds are assessed to be occupied by patients in stage one, 48.43% by patients in stage two, and the remaining beds are taken up by long-stay patients. It is evident that even though only 1.6% of the patients necessitate long-stay treatment, they end up occupying 12.35% of the total bed capacity. These findings are aligned with those reported by other authors [9, 42].

The average daily discharge rate from each corresponding stage of patient care can be derived using Equation 7 (Appendix A). It can hence be deduced that the Orthopaedic department can discharge/admit approximately 1.8 patients per day. Most of these can be attributed to the discharge of patients post-operatively in stage two; less than 0.2 (one every four days) per week can be foreseen to be discharged from stage three care. This demonstrates the difficulties encountered in freeing up beds to accommodate new patients. Stagnant discharge rates of patients in stage three are a rate-limiting factor that needs to be circumvented.

2.4. Utilising the SD Model as a Heuristic in Policy Development

It has been established that SD modelling can establish the comparative benefits and economic feasibility of proposed interventional policy amendments (what-if scenarios), hence abolishing the need for economically unsound, risky direct experimentation [53]. This is especially relevant to the widespread use of SD models as a conduit, which could potentially impact the allocating of essential resources optimally by policy generators [49, 54-56]. The salient aspect of unlocking this process is the potential of models to display features of unforeseen consequences before investing in concretised changes [29]. The model utilised can be of benefit to explore some 'what-if-scenarios'. According to Chaussalet, et al. [42] a patient's average LOS (Length of Stay) in each of the three phases can be calculated by $1/\mu i$, which is LOS. The researcher has experimented with altering the values of the service rates ($\mu 1$), ($\mu 2$), and ($\mu 3$) corresponding respectively to stages one, two and three - which have a direct bearing on the allocation of beds in each of the three stages.

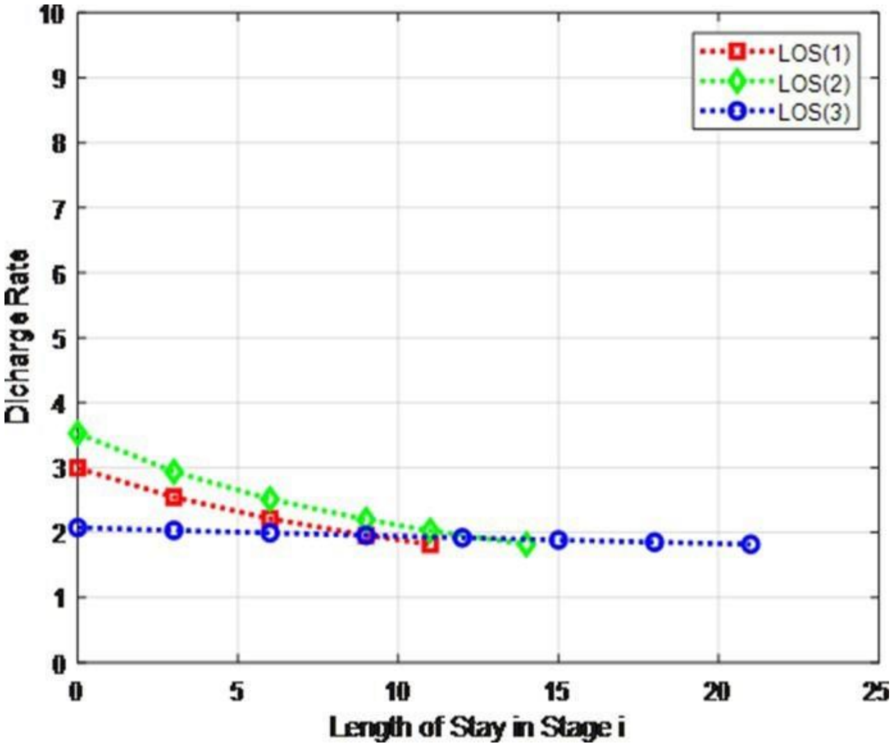

Figure 3.
Length of stay in each stage vs. discharge rate.

Figure 3 illustrates the graph plotted to generate details about accelerating the time spent in stage one, i.e. increasing (µ1). This will incrementally increase patients' proportion of beds in active usage in stages two and three, i.e. this would be detrimental since it would mean the time taken from the date of admission to the theatre is increased. Sometimes, this phenomenon manifests when access to the theatre is delayed due to staff shortages, elevators, or air conditioners not being operational, as has been reported about structural limitations at Addington Hospital [57]. Since the average LOS in stages two and three is higher than in stage one, this intervention may compromise the functional capacity to admit new patients by way of blocking beds.

A scenario that reduces the average LOS in stage three, i.e. effectively increasing (µ3), will result in a relative rise of beds made accessible to patients in stages one and two. This will create the desired effect of reducing the average LOS and unblocking the bed availability. This is congruent with findings by Chaussalet, et al. [42] who described scenarios which will unblock a more significant number of beds if frameworks could be contextualised in terms of addressing why patients spend prolonged periods admitted into stage three, i.e. long-term stay. The PAR Reflection points below will discuss some of these causative factors.

Examination of the graph in Figure 3 further unmasks the finding that alterations in µ's have a limited influence on the department's overall daily admission (discharge) rate. Figure 3 depicts the curves for (µ1) and (µ3), which almost overlap. This can be explained by appreciating that these rate alterations display similar trends. Hence, if the hospital manager is under duress to increase the daily admission (discharge) rate of the Orthopaedic wards per day, altering the average LOS in each stage will be found not to have any statistically significant change on the capacity to admit new patients (Figure 3). However, a decrease in the inter-phase transfer probabilities displays a far more significant overall impact on the daily admission rate figures depicted in Figure 4.

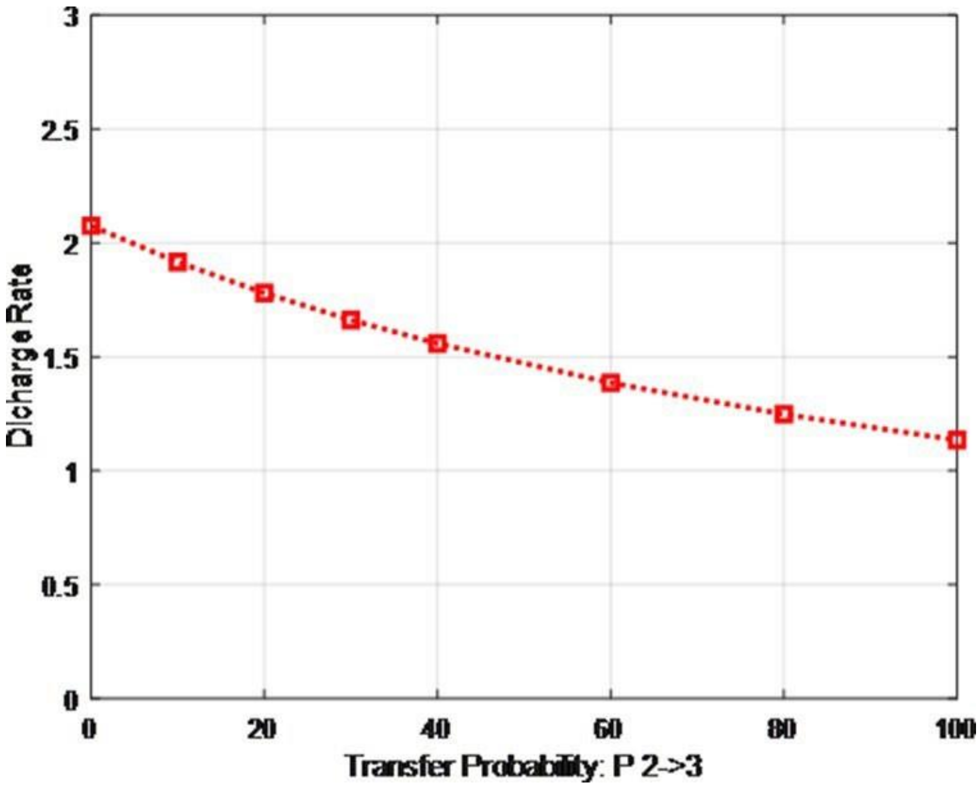

Figure 4.
The effects of decreasing transfer probability in (P2, 3).

Whilst increasing the discharge probability in stage one can result in speeding up the daily discharge figures, the literature [19, 27-29] cautions against this since this could give rise to an unforeseen consequence of eliciting complications in patients discharged prematurely. For instance, relative to the Orthopaedic context, a premature discharge of a patient who requires extensive wound care may result in the patient being readmitted with florid sepsis of the infected area.

Hence, a reduction in the stage two transfer probability (P2, 3) in Figure 4 is a more plausible, safer clinical alternative. As an added feature, this option will secure more beds, which can be utilised for stages one or two. Decreasing transfer probabilities in (P2, 3) (Appendix A) demonstrates the most significant impact in terms of improving the overall daily discharge rate and freeing up beds which would have been occupied by patients in stage three to be distributed between patients in stages one and two.

Reducing the LOS in stage two generates an output of the highest discharge rate and greater capacity for new admissions. The ideal situation would be decreasing the transfer probability (P2, 3) to 0%, freeing up the most significant number of beds, as in Figure 5.

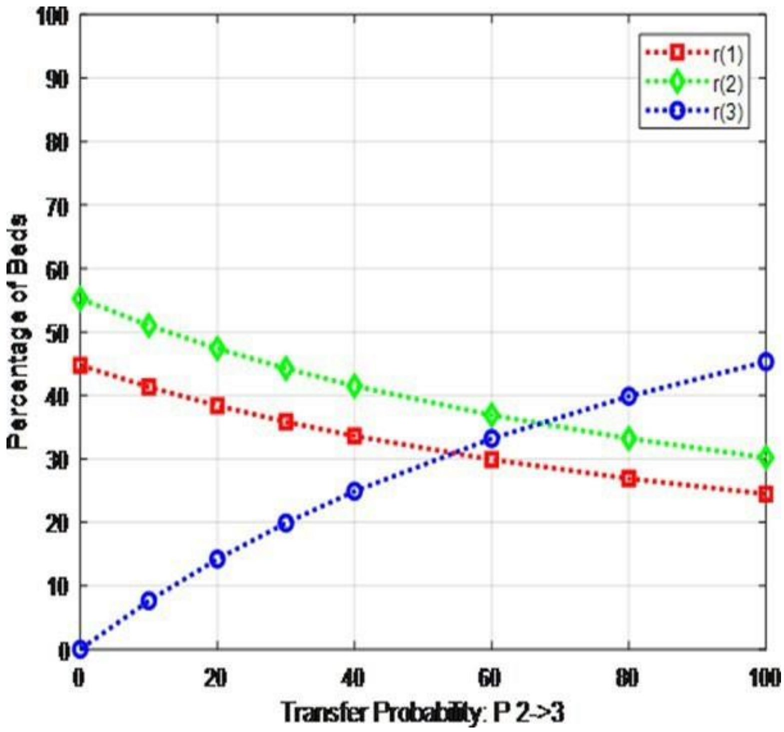

Figure 5.
The effects of the percentage of bed allocation to stages 2 and 3 by decreasing transfer probability (P2, 3).

In the realm of probing 'what if scenarios', if hypothetically there were no bed constraints and the bed capacity could be increased just by 10 per cent, advancing up to a generous 50 per cent increase, the graph generated reveals some interesting findings (Figure 6). Stakeholders and participants involved in this study were able to visualise the risk-free model simulation and responded as follows:

> We have become accustomed to limited bed availability and the necessity to reallocate our resources; hence, it's crucial to comprehend the ramifications. Frequently, we implement changes without fully grasping their implications, which precisely underscores the rationale for employing simulation. (Participant 3; Medical Doctor)

> What I find promising here is the ability to envision what's achievable. If I were the CEO (Chief Executive Officer), I would contemplate redistributing some of the demand across various areas and pools. While we have a basic understanding of this concept, I can visually discern the actual effects. (Participant 5; Medical Manager)

The participants' views indicate that the participatory modelling process enhances and strengthens a cross-collective reaction towards public healthcare reform. Incorporating an array of sectors to engage in the participatory procedure allows various stakeholders to be incorporated. This, in turn, may enhance the responsibility placed upon leaders at regional and national levels. The objective is to facilitate more strategic, enduring choices regarding optimal employment of scarce funds to enhance coordination and efficiency across multiple sectors [58]. The outcome is delivering maximum advantage with minimal risk to the system.

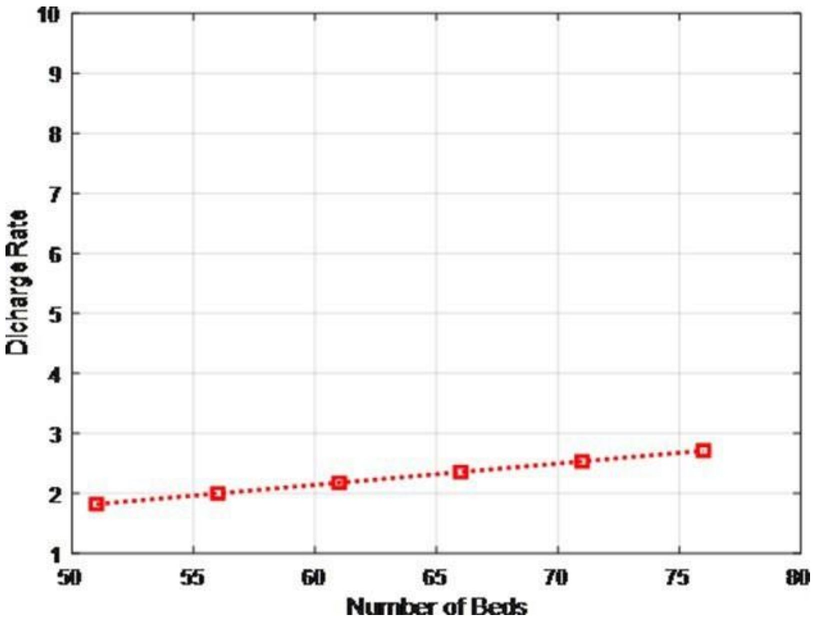

Figure 6.
What if scenario' of increasing bed capacity vs. discharge rate.

Now, when the bed capacity is increased even by 50 per cent, the analysis of the discharge rate displays an improvement. However, when these results are compared to those generated in Figure 4, it is evident that the percentage increase is not as effective as that of decreasing transfer probabilities in (P2 3) (Appendix A). Therefore, if transfer probabilities are decreased between stages two and three, e.g. reducing (P2, 3) from 17% to about 0%, the discharge rate increases to 114%. This can be compared to bed constraint variable K, which increased by 17%, raising the discharge rate by 118 per cent.

Although the two interventions are comparable, one requires significant resources (i.e., increasing bed parameters) and fiscal expenditure instead of taking care of inter-stage probability transfers and selecting one option over the other results in huge budget implications for the hospital. This lends huge implications and gravitas to the idea that medical managers should not just throw money at a problem, i.e. a 'stock increase' policy. Instead, the effects thereof should be analysed in a rigorous scientific manner. Hence, this model has been able to demonstrate this quite successfully. The examples above demonstrate potential routes that could aid policymakers in formulating more thorough, informed decisions by considering the effect of alterations to specific parameters on the overall efficacy of patient flow through the system.

Table 2.
PAR reflection point 9.

PAR Reflection Points
Investigating stage three delays
The graphs above (Figure 3) depict the importance of analysing and understanding why patients spend excessive time in stage three since this significantly affects the overall discharge and admission rates. During the data collection process, rate-limiting factors related to the length of waiting time in the ward post- discharge of patients or waiting to be transferred to alternate step-down facilities were explored. Some of the oft-quoted feedback from staff in the Orthopaedic Department was related to issues pertaining to step- down facilities or the scarcity of securing efficient social services in place of homeless patients.
Accommodating patients with complex bio-psycho-social needs
The researcher has engaged with social care services at Addington Hospital on how meaningful solutions can be arrived upon to secure placement for patients with no fixed abode. These negotiations were fraught with bureaucratic and upstream impediments to funding the social service department. At this stage, the researcher does not have much agency to intervene. Nevertheless, ongoing discussions will ensue on working out paradigms that benefit all patients.
Long-term rehabilitation facilities
The overall daily admission rate can also be ameliorated by establishing secure, well- equipped 'step-down' facilities for patients to be discharged to receive physiotherapy and other specific healthcare requirements optimally, e.g. wound care or prolonged bed rest, which requires a relatively protracted stay. Other studies also display a correlation between delayed discharge due to a lack of securing long-term care arrangements for patients [3, 9, 19].
Expediting discharges
Discharges should be expedited post-operatively by carefully considering the clinical context of the patient such that the discharge is not premature. Instead, they receive optimal post-operative rehabilitation and are discharged promptly. This prevents/shortens the time spent in stage three, making more beds available in stages one and two. Often, a stumbling block in this stage is the lack of post-op physiotherapy walking aids.

2.5. Limitations of SD Models

After dissecting the factors related to impediments in the patient flow process, a closed queuing network model was adapted mainly for its utilitarian aspect of considering Addington Hospital's constraints bed capacity. Whilst the outputs generated through the rigorous mathematical process deepened awareness of patient flow processes, relevant literature pertinent to SD models cautions that underlying factors that enable practical model usage are not primarily known. Models generated should possess qualifying features concerning their realism, robustness, flexibility and potential to generate insightful conclusions. These numerous requirements should consistently ensure that a model is reliable and can be depended upon for studying oscillations in the system and carving out niche areas in policy development [5, 59].

In the context of this study, specific limitations include the aggregation of all orthopaedic conditions into a single model, which may obscure condition-specific flow dynamics, and the exclusion of staff availability as a dynamic variable; despite its known impact on discharge timing, operating theatre access, and ward throughput. These simplifications were necessary to preserve model tractability but may limit the granularity of scenario testing and real-time responsiveness.

These ambiguous results can be attributed to several identifiable factors, including non-engaging managerial style, rigid organisational structure, inaccessibility to data, poor interdisciplinary collaboration and a distinct paucity of strategic clarity [8, 40, 60, 61]. Hence, many collaborative efforts to apply system dynamic-inspired transformation have failed [62, 63]. Simulation modelling has gained extensive usage in healthcare applications since the 1960s and is employed by academic institutions and commercial consulting firms. Nevertheless, despite numerous survey papers spanning several decades documenting SD models in healthcare, it is estimated that only five per cent of these models significantly influence real-world implementation [64, 65]. According to Holmström, et al. [65] this phenomenon can be attributed to straightforward models or conventional implementations of established methodologies being more prone to practical adoption. However, papers outlining these models often face challenges in gaining acceptance for publication since editorial teams of journals typically base their decisions on the originality of the scientific or technical content rather than the derived practical utility of the findings.

3. Conclusion

Given an understanding of the practical challenges of the inner working realities of Addington Hospital, i.e. bed constraints and high bed occupancy rates, the researcher embarked on adopting a utilitarian approach to addressing these limitations directly. The closed queuing network was adapted and utilised, revealing the inter-dynamics of altering relevant parameters. The researcher wishes to tentatively assert that this model is well suited to assess the long-term policy changes by adapting model parameters such as LOS in each phase of patient care, transfer probabilities and bed allocation during the various stages of patient care. This could garner more solutions for addressing the blockages of beds from the ED to the Orthopaedic wards, thereby facilitating the admission of more elective patients. This can potentially ease the obstruction of bed flow, as alluded to in the problem statement of this research paper. By reducing delays in Stage 3, the system can reclaim a predictable proportion of bed capacity, thereby safeguarding space for elective surgery patients who are routinely displaced by unpredictable emergency admissions; a core challenge identified in the problem statement. The participatory research methodology employed in this model holds potential for the Orthopaedic department within this hospital and addresses patient waiting time in other Orthopaedic departments across the country. Moreover, the findings can offer valuable insights to enhance the efficiency of various hospital departments, extending beyond Orthopaedics.

3.1. Reflexivity Statement

Self-reflexivity, engaging in a meaningful analysis of one's identity and experiential realities within power systems, assisted stakeholders in expressing their principles and understanding the influence of authority and perceived advantages on research practices. This insight generated the exploration of multiple dimensions of work and envisioning greater pluralistic and egalitarian modalities of engaging with other participants which ranged from Senior Management personnel, to attending ward doctors, nursing staff and patients coming from diverse backgrounds in the South African Durban milieu. Cultivating an appreciation for diverse cultures and embracing ethics of societal justice was considered essential for questioning preconceived views, acknowledging power dynamics, and challenging dominant cultural assumptions.

At the intersectoral meso level, it was considered imperative to critically evaluate the structures of stakeholder representation to generate a valuable understanding of the partnerships and conflicts within the hospital research environment. Comprehending grassroots associations' landscape, roles, functions, and connections between "representatives" and broader communities was pivotal. This understanding helped assess the presence of suitable inclusive frameworks and the potential for the hospital population to collaborate successfully, placing aside their disparities and working towards a common goal.

Collaborative research's true essence and significance lie in its capacity to ignite change-driven initiatives for enhanced social justice. Hence, a supportive socio-structural environment was considered vital at the macro level for realising this potential. Participatory research is more likely to succeed in contexts where state institutions facilitate meaningful participation of previously under-represented populations, e.g. patients and where grassroots initiatives have previously demonstrated the ability to effect systemic changes.

Abbreviations:

SD – System Dynamics
PAR – Participatory Action Research
LOS – Length of Stay
ED – Emergency Department
CLD – Causal Loop Diagram

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Appendix A.
Sd Modeling Derivatives.

$e_i = \prod_{j=1}^{i-1} p_{j,j+1},\ i = 2, \dots, M$	(1)
$r_i = \dfrac{\frac{e_i}{\mu_i}}{\sum_{i=1}^{M} \frac{e_i}{\mu_i}},\ i = 1, \dots, M$	(5)
$EL_i = Kr_i$	(6)
$ED_i = p_{i,1}\mu_i EL_i$	(7)
$ED = \dfrac{K}{\sum_{i=1}^{M} \frac{e_i}{\mu_i}}$	(8)

```
% This script models:
% - the expected number of patients per phase
% - the expected discharge rate per phase
% at the Dept of Orthopaedic Surgery at Addington Hospital given the input

% Author: Dr Maseeha Ansermeah

clearall; clc;

% M is number of phases the patient goes through in hospital. M = 3;% M set in the paper.
% K the total bed capacity of the Orthopaedic Wards, Addington.
K = 60;

% LOS is the length of stay per phase in days LOS = zeros(1,M);
LOS(1) = 11;% LOS in phase 1 LOS(2) = 14;% LOS
in phase 2 LOS(3) = 21;% LOS in phase 3

% r is the proportion of patients in phase i r = zeros(1,M);

% AvgL is the expected number of patients per phase i AvgL = zeros(1,M);

% VarL is the variance of the number of patients per phase i VarL = zeros(1,M);

% AvgD is the expected discharge rate per phase i AvgD = zeros(1,M);

% VarD is the expected discharge rate per phase i VarD = zeros(1,M);

% p(j->j+1) is the transfer probability from phase j to phase j+1
p_0_1 = 93/100; p_1_2 = 97/100;
p_2_3 = 17/100;

% e(i) is the arrival rate per phase i, calculated using Equation 1
e = zeros(1,M);
```

```
e(1) = 1;
e(2) = p_1_2;
e(3) = p_1_2*p_2_3;

% r(i) is the proportion of patients in phase i, calculated from
% Equation 5

r(1) = ( LOS(1)*e(1) )/( LOS(1)*e(1) + LOS(2)*e(2) + LOS(3)*e(3) );
r(2) = ( LOS(2)*e(2) )/( LOS(1)*e(1) + LOS(2)*e(2) + LOS(3)*e(3) );
r(3) = ( LOS(3)*e(3) )/( LOS(1)*e(1) + LOS(2)*e(2) + LOS(3)*e(3) );

% AvgL(i) the average number of patients in phase i, calculated using
% Equation 6

AvgL(1) = K*r(1);
AvgL(2) = K*r(2);
AvgL(3) = K*r(3);

% VarL(i) the variance of the average number of patients in phase i,
% calculated using Equation 6

VarL(1) = K*r(1)*(1-r(1));
VarL(2) = K*r(2)*(1-r(2));
VarL(3) = K*r(3)*(1-r(3));

% AvgD(i) the discharge rate in phase i, calculated using Equation 7
AvgD(1) = p_0_1*(1/LOS(1))*AvgL(1); AvgD(2) = p_0_1*(1/LOS(2))*AvgL(2); AvgD(3) = p_0_1*(1/LOS(3))*AvgL(3);

% VarD(i) the variance of the discharge rate in phase i,
% calculated using Equation 7
VarD(1) = p_0_1*(1/LOS(1))* sqrt(VarL(1)); VarD(2) = p_0_1*(1/LOS(2))* sqrt(VarL(2)); VarD(3) = p_0_1*(1/LOS(3))* sqrt(VarL(3));
%
% e
% LOS
% r
% AvgL
% sqrt(VarL)
% AvgD
% VarD

% Expected Daily discharge/admission rate, calculated using Equation 8

SystemD = K/( LOS(1)*e(1) + LOS(2)*e(2) + LOS(3)*e(3) );
```