Manuscript title

A system dynamics approach to workload management of hospital pharmacy staff: modelling the trade-off between dispensing backlog and dispensing errors

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Occupational Applications

We adopted a system dynamics approach to simulate dynamic factors affecting dispensing backlog and dispensing errors in a hospital pharmacy system. This approach allowed us to simulate diverse scenarios (hospital winter pressures and differing staffing arrangements) and to understand the potential unintended impact of rework due to dispensing errors, which is often missing from model-based approaches. The results revealed the impacts of key factors (high workload, staff capacity, backlog, incoming prescriptions, errors, and delay) on system performance and safety within hospital pharmacies. Use of a system dynamics model can provide pharmacy management with practical tools to understand the unintended adverse effects of dynamic factors that contribute to dispensing backlog and errors.

Technical Abstract

Background (or Rationale): The traditional hospital pharmacy staffing management model does not account for the complex interactions of social, technical, and environmental factors that can affect performance and safety. Conventionally, workload and dispensing errors within the hospital pharmacy system have been analysed on a factor-by-factor level, using linear and static approaches that ignore feedback mechanisms.

Purpose: We aimed to explore the potential of a system dynamics approach to modelling staffing level management in a hospital pharmacy.

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Methods: Qualitative and quantitative system dynamics models were created to simulate dynamic aspects contributing to dispensing backlog and errors in a hospital pharmacy. A baseline scenario was tested in a "normal" condition, and three different staffing level scenarios (fixed, flexible, and equivalent-fixed) were tested in an extreme condition (hospital winter pressures).

Results: During hospital winter pressures, the unintended negative effect on rework due to dispensing errors made it more challenging to deal with demand variability. Findings from the scenario-based simulations revealed that a flexible staffing level arrangement, which dynamically adjusts the number of staff to demand variability during winter pressure, is less effective in reducing the amount of rework than maintaining an equivalent-fixed staffing level. Dispensing backlog during winter pressure can be averted or substantially diminished by proactively employing an equivalent-fixed staffing level that accounts for total staff capacity needed vis-à-vis the current workload. Premature release of extra staff and delayed calling of additional staff from wards can have significant impacts on backlog.

Conclusions: Our results demonstrate that system dynamics can provide practical insights into staffing level management in a hospital pharmacy, by accounting for dynamic factors causing dispensing backlog and errors and presenting decision-makers with a holistic understanding of elements affecting system safety and performance.

Keywords: systems analysis, computer simulation, pharmacy dispensary

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1. Introduction

Recent evidence has revealed growing concerns that community pharmacists' workload and frequent dispensing errors are interlinked (Jacobs, Johnson, & Hassell, 2018). These concerns are corroborated in the literature that has examined the frequency and causes of a number of dispensing errors in hospital and community pharmacies (Aldhwaihi, Schifano, Pezzolesi, & Umaru, 2016; James et al., 2009; Peterson, Wu, & Bergin, 1999). The most frequently identified factor is high workload (James et al., 2009). Interruptions, inappropriate skill-mix, poor handwriting, inadequate staffing levels and level of pharmacy knowledge have also been identified as contributing to dispensing errors (Ashcroft, Quinlan, & Blenkinsopp, 2005; James et al., 2009). Other studies have found that high workload, combined with low staffing levels, leads to circumstances in which errors are made (James et al., 2008; James, Barlow, Hiom, Roberts, & Whittlesea, 2008) . More significantly, any work becomes more effortful when the factors above are added to the existing pharmacy staff workload. Errors may be difficult to avoid when a safety culture de-emphasises safety and instead prioritises competing concerns such as staffing cost and efficiency (Litvak et al., 2005).

The extent of incidents caused by complex relations involving technical, social, and environmental factors have unveiled the limitations of traditional staffing and safety management approaches (Anacleto, Perini, Rosa, & César, 2007; Ashcroft et al., 2005; Beso et al., 2005; Bond & Raehl, 2001; Gidman, Hassell, Day, & Payne, 2007). Studies of nurse-to-patient ratios have found that adequate staffing is associated with fewer adverse patient outcomes, such as in-hospital deaths, urinary tract infections, pneumonia, and shock or cardiac arrest, along with reduced lengths-of-stay (Aiken, 2002; Needleman, Buerhaus, Stewart, Zelevinsky, & Mattke, 2006). Amongst short-term general hospitals in the U.S., over 70,000 fewer adverse outcomes were recorded when an adequate staffing level was enforced (Aiken, 2002; Needleman et al., 2006). In contrast, less adequate staffing levels – indicated by workload, overtime, or increased nonregistered nurse hours of care – resulted in unexpected patient harm (Kc & Terwiesch, 2009) and medication errors (Seago, Williamson, & Atwood, 2006). Berwick's (2013) review of patient safety stressed the critical need for introducing

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systematic methods and regulation on correct staffing levels based on a dynamic understanding of existing staff workload.

System dynamics (SD) is a robust analytical modelling approach that looks at complex non-linear issues. Its origin is derived from Forrester's (1961) seminal work on "industrial dynamics". SD utilises qualitative and quantitative aspects to address and enrich understanding of complex system behaviour. The qualitative aspect, formally known as a "causal loop diagram", is a causal map in which the system organisation and the relationship between elements of a system are discovered. The quantitative aspect, formally known as a "stock-and-flow diagram", is a computer model in which relevant information and flows of the system are modelled, and behaviours are identified. Such computer models can serve as an interactive experiment wherein alternative scenarios are explored. SD address limitations of conceptual system models, such as the Systems Engineering Initiative for Patient Safety (SEIPS; Carayon et al., 2006), by simulating the critical elements quantitatively within the system and thereby allowing the behaviour of the system (and its subsystems) to be both represented and simulated.

The SD methodology has been used outside the original focus on industrial settings, in several fields of study such as healthcare (Dangerfield, 2014), defence (Coyle, Exelby, & Holt, 1999), and energy (Corben, Stevenson, & Wolstenholme, 1999). SD has been applied to various issues affecting healthcare since the 1980s (Ibrahim Shire, Jun, & Robinson, 2018), including disease epidemiology (Anderson & Anderson, 1994); patient flows in emergency and extended care (Lattimer et al., 2004; Xiao-yan & Jian-hua, 2010); healthcare capacity and delivery (Chong et al., 2015; Homer, 1984; Morris, Ross, & Ulieru, 2010; Taylor & Dangerfield, 2004); medication safety (McDonnell, 2005); and maintenance organisation planning (Guo, Roudsari, & Garcez, 2013; Kontogiannis, 2011). Previous work by the current authors (Ibrahim Shire et al., 2017) indicated that SD can be a useful tool for determining the appropriate staffing levels in a hospital pharmacy.

In areas other than healthcare, such as software development, staffing level management has been supported using an interactive simulation game that evaluates the impact of staffing policies on quality assurance and reworks (Barlas & Bayraktutar, 1992). Similarly, Abdel-Hamid (1989; 1988, 1993; 1992) has applied SD-based simulation to the staffing management of a real-world software project. However, to our knowledge, SD has not been utilised to understand the staffing level management issue in healthcare.

Within healthcare, the complexity of hospital pharmacies is evident as they deal with different types of prescriptions, employ a wide range of staff with different possible combinations of roles, and incorporate many advanced technological solutions to improve the accuracy and speed of drug dispensing. The SD approach may help decision-makers understand the complexity and the nonlinear dynamic behaviours of staffing level issues in hospital pharmacies. Therefore, this study explored the potential of an SD approach to staffing level management, constructed on a dynamic understanding of staff workload. Qualitative and quantitative system dynamics models were created to simulate dynamic aspects contributing to dispensing backlogs and errors in a hospital pharmacy.

2. Methods

The current study is based on the workflow of a hospital pharmacy dispensary (see Figure 1) in a teaching hospital in England. This hospital is comprised of ~ 1,000 beds and one dispensary. The dispensary determines staff schedule and skill-mix on a weekly basis, with a minimum staff ratio of five labellers to two checkers. The mean incoming prescription rate is 40 prescriptions per hour, which is completed using a robotic dispensing system. An SD model was developed using a participatory framework through multiple group sessions. A conceptual qualitative model was formulated initially, and was then converted to a quantitative model for four scenario-based simulations. All participants in the current study provided informed consent, as approved by the Ethical Approvals (Human Participants) Sub-Committee at Loughborough University.

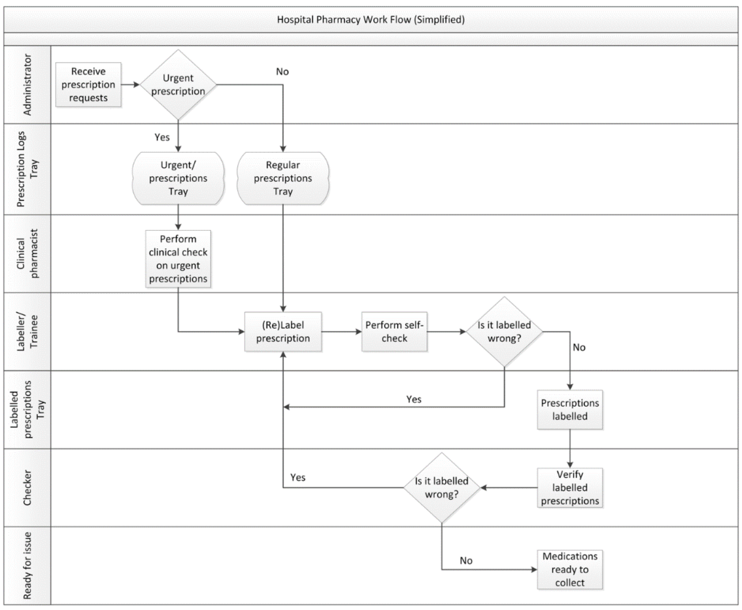

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Figure 1. Dispensing prescription work flow (simplified)

2.1 SD framework

Figure 2 shows the participatory SD modelling process which we adopted. This process was based on several key steps from two different participatory SD frameworks developed by Vennix (1996) and Andersen & Richardson (1997). The modelling cycle is not necessarily sequential and can often involve skipping steps. There are three key stages during the participatory SD cycle: 1) preparatory activities, which involve stakeholder analysis, and preliminary interviews; 2) group-based modelling workshops for model formulation and validation; and 3) follow-up activities for scenario testing and evaluation. Table 1 illustrates the number of participants involved in our participatory model building process, their roles, and the total time for each session.

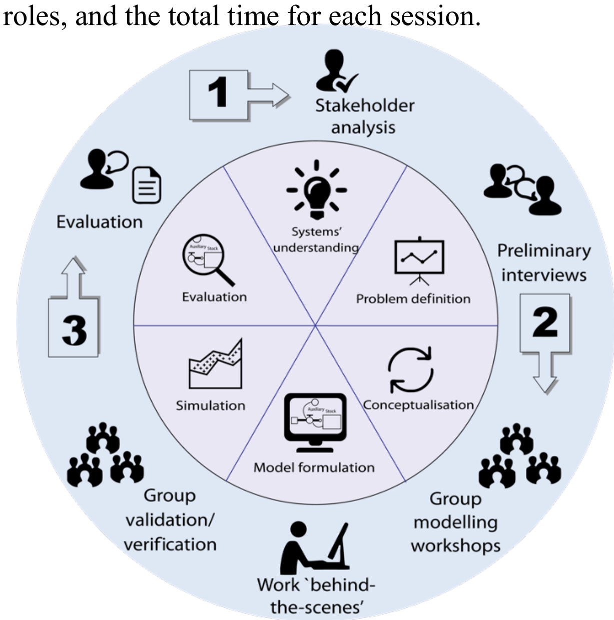

Figure 2. Modelling process using participatory system dynamics modelling (adapted from Vennix, 1996) and Andersen & Richardson, 1997))

Table 1. Participants in the participatory SD model building process

Stages	Roles	Number of participants	Time conducted
Preparative activities (preliminary interviews)	Administrators	2	1 hour each
	Labellers	4	
	Checkers	3	

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Group-based modelling workshop	Labellers	4	1.5 hour (single group session)
	Trainees	7	
	Checkers	2	
Scenario testing and evaluation	Labellers	3	Three 1.5-hour group sessions
	Checkers	5	
	Managers	13	One 2-hour session

The first stage of the model formulation was based on findings gained through stakeholder analysis and preliminary interviews with administrators, labellers, and checkers. This stage helped to articulate the current understanding of the situation, share this understanding with the stakeholders, and guide data collection in the next stage. Results from each of the interviews were coded to formulate causal links and models (Bryson, 2004), which provided clarity of thoughts by the problem owners and the modeller. The second stage, the participatory modelling process, was conducted with 13 participants, including labellers, trainees, and checkers, through multiple group model building/validation sessions over 12 weeks, which is considerably shorter than many other participatory modelling processes (Antunes, Santos, & Videira, 2006; Otto & Struben, 2004; Stave, 2002; Tidwell, Passell, & Conrad, 2004).

In the third stage, four scenarios were tested that differed in the staffing level arrangement. These tests were completed with stakeholders, and their feedback was obtained in the group sessions. Feedback obtained from the group sessions indicated that the model is suitable as a tool for demonstrating the effects of inadequate staffing levels. There was an acknowledgement that the simulation would still be of value in learning or even policy-making when set in an abstract context, although there was a greater appreciation of the model in its present real-world form. Much of the underlying discussion pointed toward using the model to assist with decision-making. Some participants stated that seeing the model outputs helped them to understand the complexity of the backlog, rework, and staffing levels problem.

The causal loop diagram was converted into a mathematical model consisting of 13 stocks (e.g., prescriptions, staff) and 26 flows (e.g., labelling rate, checking rate, error rate), with components connected by auxiliary variables (e.g., incoming prescriptions, capacity levels) to form an interconnected set of co-flows. The model was used to capture an imbalance of efficiency (reduced staffing costs and high dispensing rate) and thoroughness (minimum dispensing errors and staff well-being) affecting system operation and its actual effects on system changes. Dispensing errors and backlog were selected as two main outcome measures: dispensing errors reflect the actual amount of both detected and undetected errors made by the labellers, and dispensing backlog denotes the amount of incoming prescriptions that have not yet been labelled.

We developed the base model using exogenous inputs (e.g., incoming prescriptions, number of labellers, acceptable workload) that were derived from interviews with labellers and checkers, evidence in the literature, and hospital pharmacy databases. Several types of verifications were performed, including sensitivity analysis, logical tests, and face-validation by experts. The baseline model was validated with data derived from the hospital pharmacy dispensary database, where available. We developed interactive sets of configurations, allowing practitioners to modify the standard parameters in the model to match different workloads, such as the number of incoming prescriptions and the number of staff.

2.2 Data sources

Three main sources of input data for the model were obtained from the hospital pharmacy dispensary database. First, the urgent and non-urgent prescriptions received per hour. Second, the minimum number of pharmacists (labellers and checkers) required to run the hospital dispensary. Third, the incidents data revealing the number of errors made by each labeller and checker. Finally, if data regarding a model parameter or relationship was limited or unavailable, estimates by subject matter experts (SME) were used instead. Senior pharmacy practitioners and managers represented the SMEs.

2.2.1 Workload parameter

Workload in the labeller group was calculated by dividing the used capacity per hour by the current capacity per hour as shown in Equation (1).

$$(Labellers'Group)\ Workload = \frac{\text{Used capacity per hour}}{\text{Current capacity per hour}} x100 \qquad (1)$$

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The initial capacity of a labeller was set at 20 prescriptions per hour, and the capacity was adjusted dynamically based on the capacity depletion rate due to fatigue and the capacity restore rate as shown in Equation (2).

$$\begin{aligned} \mathit{Current\ capacity\ per\ hour} \; &= \text{Maximum hourly capacity (20 presciptions per hour)} \\ &\quad + \text{Capacity restore rate(inflow)} - \text{Capacity depletion rate(outflow)} \qquad (2) \end{aligned}$$

The fatigue depletion rate was set at 5% of the total capacity of the average labeller. This alteration was triggered when the average labeller works continuously at maximum workload capacity for over an hour, automatically reducing capacity by 5% of available capacity up to the minimum capacity (half of the maximum capacity). The capacity restore rate was triggered when the capacity depletion rate = 0 and capacity is less than the maximum capacity (no fatigue); in this case, capacity was restored by 10% of the missing maximum value up to the maximum capacity value. These estimated rates (5% and 10%) were derived from participant observations and interviews.

Based on the feedback from the group sessions, the current model reflects that the majority of errors are made by labellers. As a result, we have operationalised and restricted workload to labellers. The workload ratio of a labeller is measured from 0 to 100%, where 0% equals no workload, and 100% equals full workload. As the workload of the labellers is increased, their capacity to do the work is decreased, which can be expected to generate increased job stress and a gradually decreasing motivation to do the task (Jacobs et al., 2018). High workload can thus adversely affect dispensing quality, and when the dispensing error rate increases, the amount of rework increases (James et al., 2008; Teinilä, Grönroos, & Airaksinen, 2008).

2.2.2 Capacity allocation

The model contained a capacity allocation that prioritises urgent prescriptions over non-urgent prescriptions. The model first allocates the capacity needed to relabel existing prescriptions that were found to contain errors. This builds the task prioritisation in the following order: urgent relabelling; urgent labelling; non-urgent relabelling; non-urgent labelling.

2.2.3 Backlog and parameters

Backlog along with errors are the metrics used to help understand the system behaviour. The backlog is calculated by the difference between the sum of both non-urgent and urgent prescriptions waiting to be labelled and the sum of both non-urgent and urgent prescriptions that have been labelled and re-labelled and are waiting to be checked, as shown in Equation (3).

$$Backlog = \text{Sum of unlabelled prescriptions} - \text{Sum of labelled unchecked prescriptions} \quad (3)$$

The sum of urgent/non-urgent unlabelled prescriptions is affected by the number of errors identified by labellers in their self-checking process. Based on data from the hospital pharmacy dispensary, each labeller picks up two corrections per hour at 70% workload capacity. The effects of workload increase/decrease on dispensing errors are delayed by one hour. Based on the verification discussions with the labellers, they agreed that they were able to work for an hour under 100% workload pressure with standard efficiency of making acceptable labelling errors (n = 1).

The dispensing error rate and the error detection rate change in the model according to the workload. If the workload is at a constant 100% for more than an hour, the amount of labelling errors gradually increases up to 40%. On the other hand, the error detection rate decreases with increased workload. With 100% workload for more than one hour, self-checking can detect 50% of errors. For a labeller that works at a capacity of 70% workload, the self-checking success rate is 93%, as shown in Equation (4).

$$Dispensing\ error\ rate = (\text{labeller actual error rate }) \ x \ (\text{labeller selfcheck rate}) \quad (4)$$

The second phase of rework is errors detected by the checkers in the final checking stage. This is the number of errors that labellers made but undetected through self-checking but detected by the checkers. The checker’s ability to find errors again depends on their workload. At a continuous 100% workload of more than one hour, checkers’ capacity to detect labelling errors made by labellers decreases to 80% success rate.

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2.3 Simulation scenario development

We created three additional scenarios with winter pressure (see Table 2). The winter pressure is defined by exceptional surges in demand during the winter months (i.e., increased hospital patient admissions and in-coming prescriptions). The baseline scenario contained the baseline staff level allocation in a normal operation situation, prior to winter pressure: five labellers, two checkers, and incoming prescriptions data from the quieter months. Scenario 2 examined the impact on workload, backlog, and error of increased incoming prescriptions during the winter period, but with the same staffing levels (five labellers and two checkers). Scenario 3 simulated the same impact when the number of staff can be dynamically adjusted when needed. Lastly, Scenario 4 was based on utilising the fixed number of staff equivalent to Scenario 3.

Table 2. Scenarios that were tested

Scenarios	% of prescriptions pre-winter	Staff parameters
Scenario 1 - five fixed staffing under normal operation	Pre-winter incoming prescriptions	Fixed staffing levels: 5 labellers
Scenario 2 - five fixed staffing under winter pressure	150%	Fixed staffing levels: 5 labellers
Scenario 3 - dynamic staffing under winter pressure	150%	Dynamic staffing levels depending on backlog and capacity
Scenario 4 – fixed (equivalent to Scenario 3) staffing under winter pressure	150%	Average staffing levels derived from Scenario three: 8 labellers

2.4 Model Development

Figure 3 shows the interactions between the work system, processes, and outcomes of this study. Three loops were identified: two reinforcing loops (Fixed Staff and Effects of Trainees) and a balancing loop (Dynamic Staffing Levels). The first reinforcing loop is based on a fixed staffing level state, wherein the increase in incoming prescriptions due to winter pressure leads to an increase in workload, leading to a decrease in time to self-check for errors, which then leads to an increase in dispensing errors. This process leads to an increase in rework to be done, which increases the backlog and finally leads back to an increase in workload. This loop is caught in a vicious cycle of circular chain reactions, whereby the workload will keep increasing and so will the backlog. A balancing loop is introduced to remedy the aforementioned reinforcing loop, which contains a call for additional staff at appropriate times to reduce overall workload and reducing staff at appropriate times where the system regains its equilibrium

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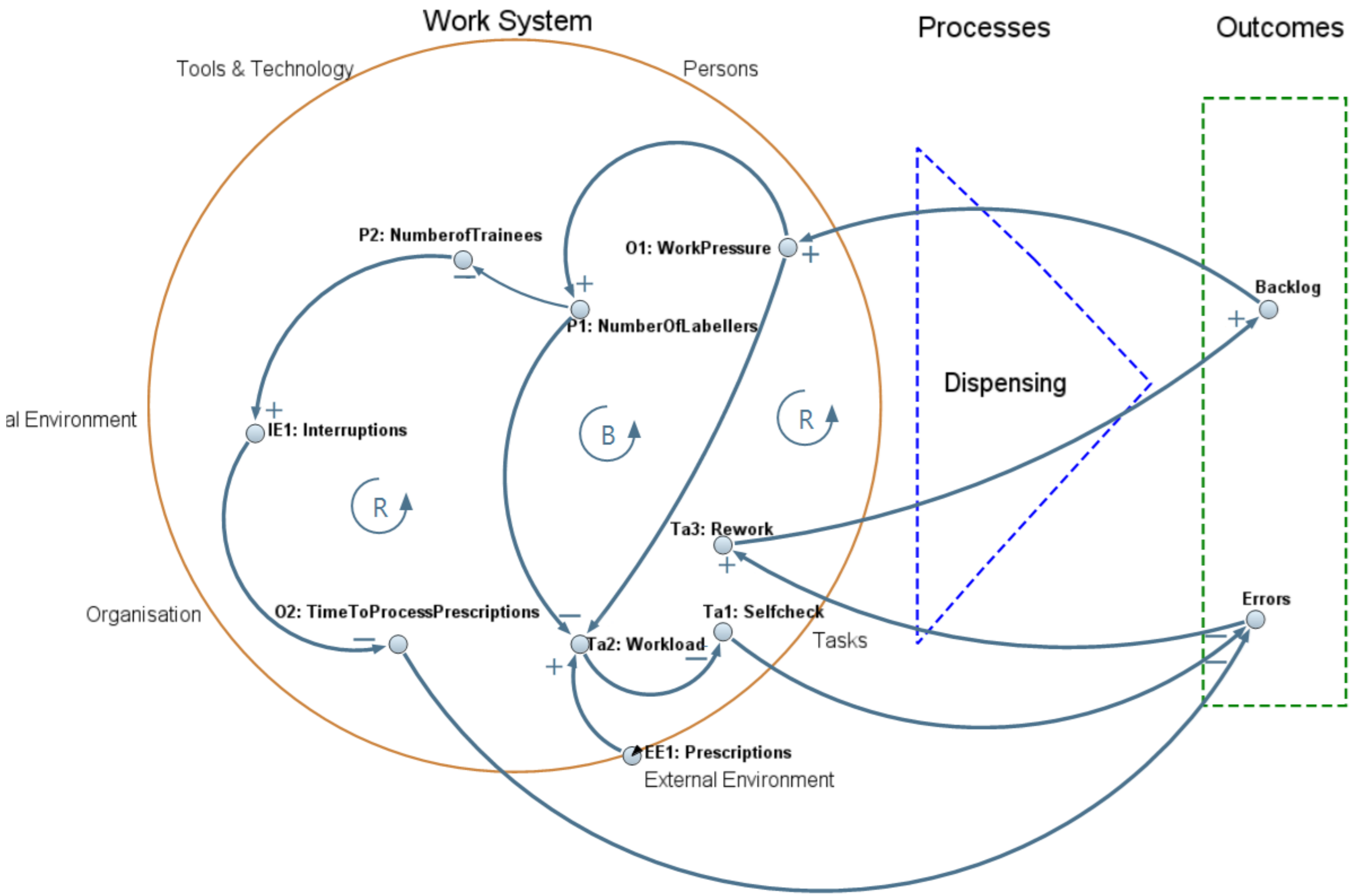

Figure 3. Causal loop diagram of a pharmacy dispensary system

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2.5 Quantitative SD Model and Simulation

We converted the abstract model in Figure 3 to a stock-and-flow diagram by using Vensim Professional software (version 6.4E, Ventana Systems, Cambridge MA). Crucial quantifiable details were added through the conversion process from the abstract model to the stock-and-flow diagram. We do not include the final stock-and-flow model in this report, due to the complexity (13 stocks, 68 variables, and 26 flows), but several key aspects of the model are discussed below.

As shown in Figure 4, urgent prescriptions are first labelled and dispensed before non-urgent prescriptions are considered. Once urgent prescriptions are received, they accumulate in an unlabelled stock and are processed. The labelling rate of urgent/non-urgent unlabelled prescriptions is affected by the number of errors found by labellers. The error rate increases the workload by a degree equivalent to the error rate as the labeller has to relabel the prescription with the error. Labellers find a certain percentage of mistakes during the self-checking process, which is the first phase of rework. The second phase of rework is errors found by the checkers in the final checking stage. These are the undetected errors that labellers made and contribute to the total rework workload.

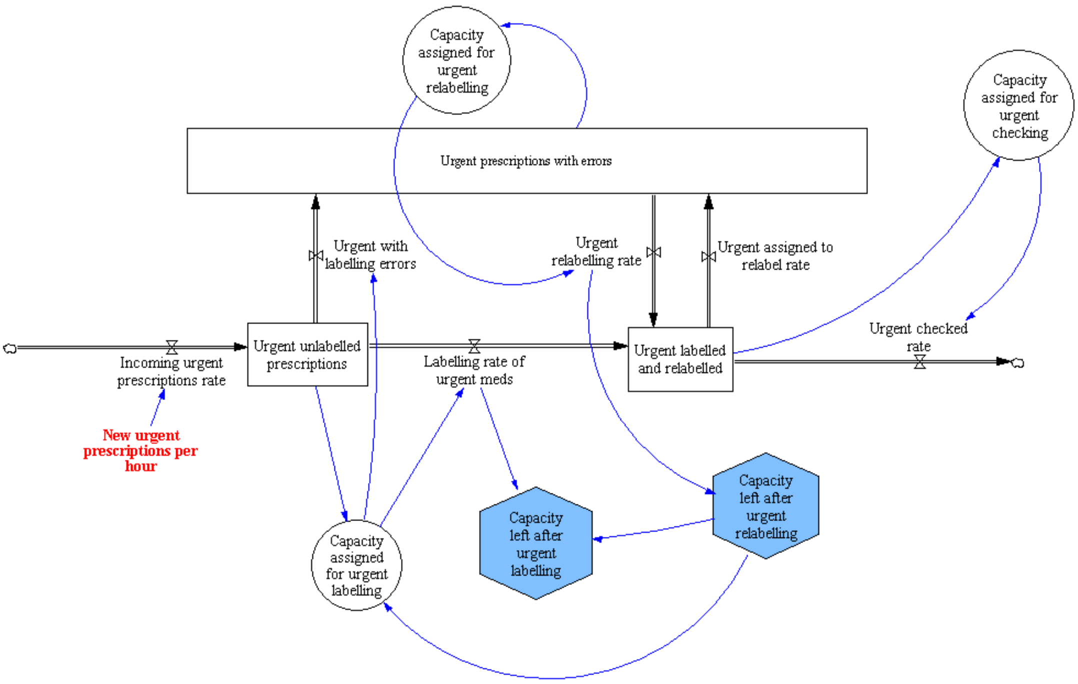

Figure 4. The process of incoming urgent prescriptions to dispensed prescriptions flow

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Figure 5 shows that the number of labellers is regulated by the total unlabelled prescriptions. The labeller stock starts with an initial number of labellers and is adjusted by ‘add labellers’ rate and ‘remove labellers’ rate. If the total unlabelled prescriptions are higher than total labellers’ capacity per hour, and the maximum number of labelling staff available is greater than current labelling staff, the model automatically adds labellers. The rate works conservatively, as it is activated when there is even a small shortage of capacity. Similarly, if total labellers’ capacity is greater than total unlabelled prescriptions, and the current number of labelling staff is greater than the minimum number of labellers, then excessive labellers are removed from the system.

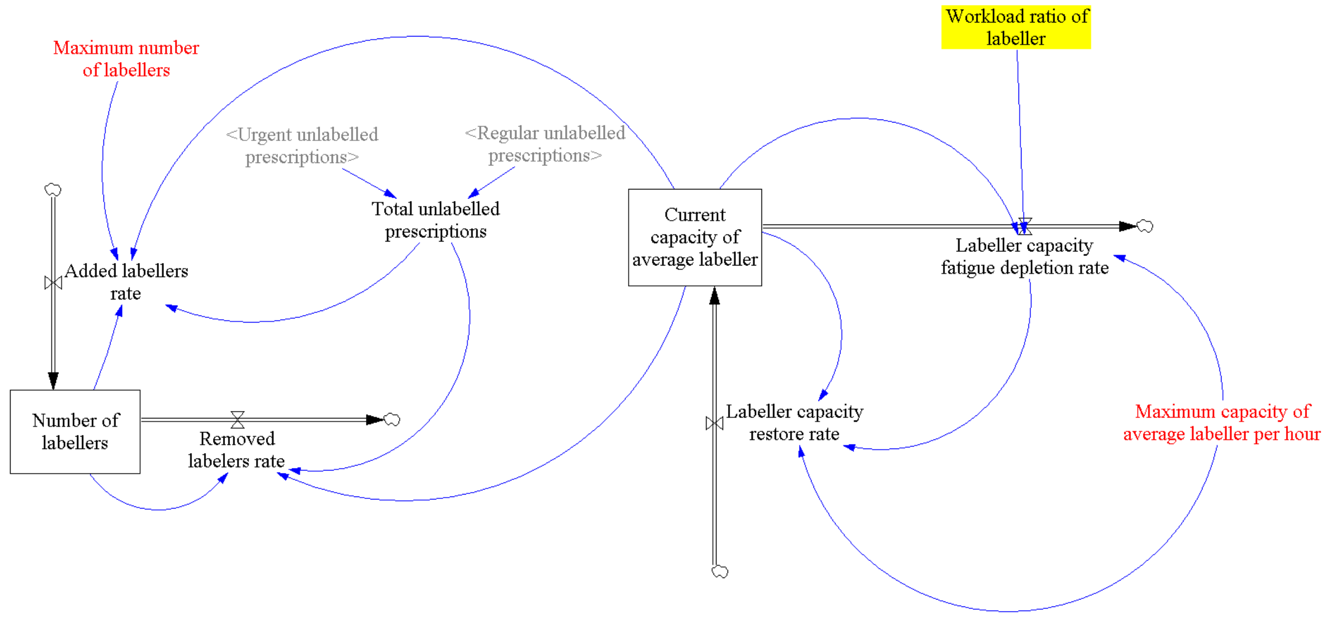

Figure 5. The dynamic labellers' process

3. Results

3.1 Scenario 1: Baseline

The baseline scenario shows the existing setup of the hospital pharmacy dispensary under normal conditions (five labellers and two checkers). Figure 6a indicates the incoming prescription rate whilst Figure 6b illustrates the outgoing prescription rate, revealing that all outgoing urgent and non-urgent prescriptions are cleared around 7 PM with such a staff arrangement. Labellers workload (Figure 6c) is substantially increased once the incoming prescriptions rate increases, and mistakes are

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made forcing labellers to relabel the medications. However, there is no reduction in their full level of capacity as the workload is below 70%. Lastly, the number of errors (self-check errors and final checking errors) increase once backlog is detected (Figure 6d), and it is for this reason that workload is slightly increased. With a base staff ratio of five labellers and two checkers, no additional staffing is needed for this level of incoming prescriptions, as backlog is substantially low and under control by the base number of staff.

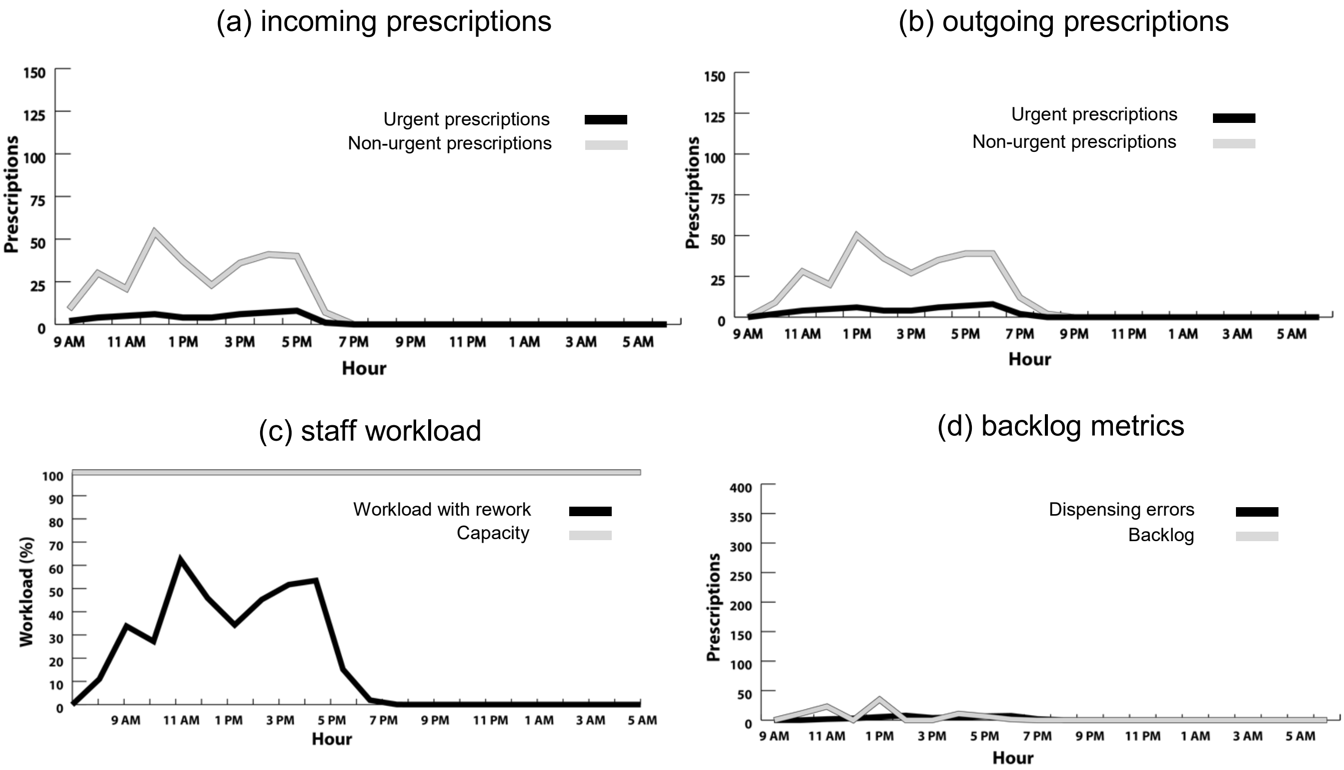

Figure 6. Results from Scenario 1 (baseline)

3.2 Scenario 2: Winter pressure using baseline staffing level

Winter pressure forces incoming prescriptions to increase by 150%, and using the same level of staffing to accommodate workload is not feasible (Figure 7a). At times, the dispensary receives more than 100 prescriptions per hour. Outgoing prescriptions with the standard staffing levels continue into the next morning (Figure 7b), and the degree of rework is increased (Figure 7c) which has an impact on workload. The workload with rework stays at 100% all the way to 1 AM. Moreover, there is a sharp reduction in the capacity of labellers as fatigue is induced, due to the continuous

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workload. Capacity is gradually restored once the workload goes below 85%. As the backlog surpasses a certain level, the number of mistakes made stabilises at the maximum number of errors that can be committed by the labellers (Figure 7d). Operating the dispensary with a baseline staffing level during winter pressure leads to a 37% increase of incoming prescriptions being re-labelled (rework).

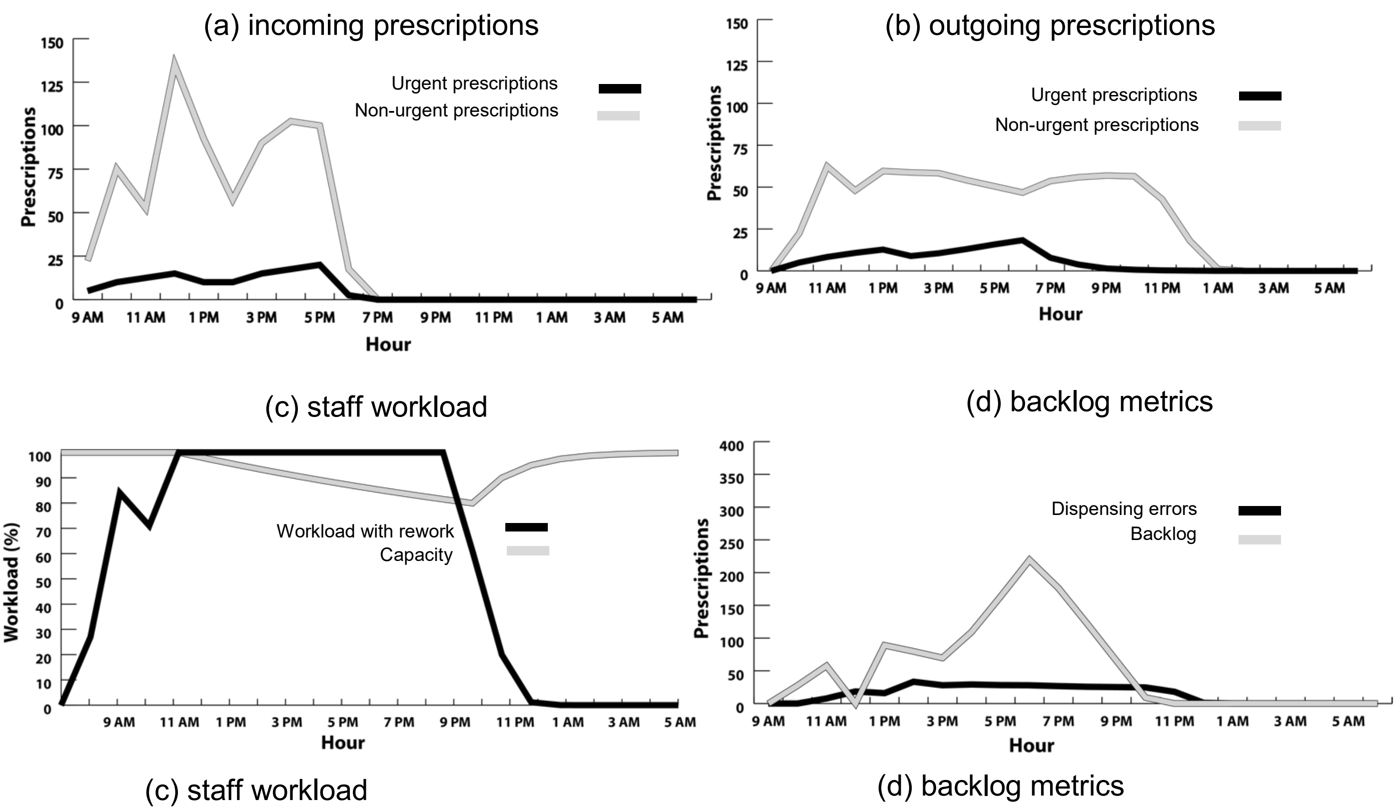

Figure 7. Results from Scenario 2 (fixed staffing under winter pressure)

3.3 Scenario 3: Dynamic staffing levels

When the dynamic staff levels switch is enabled in the model, the number of staff needed to counteract the growing backlog and reduce the high workload is calculated. Between 12 PM and 2 PM, when the backlog starts proliferating (Figure 8d), 12 additional backup staff are added to reduce the backlog, which results in 17 dedicated labellers being brought in (see Table 3). Once the backlog is significantly reduced, the staff is once again reduced at 3 PM to nine dispensers and 4 PM to the base staff level. These changes are based on the algorithm determining the number of dispensers needed to dispense the prescriptions at a normal workload pace. However, as the backlog grows again, additional backup staff are recalled from the wards, and the model calculates that a total of 15

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dispensers' capacity is needed to manage the growing backlog. Once the backlog is reduced from 5 PM until 8 PM, the base staff level remains. Although increased staff can significantly reduce the backlog and workload, the number of detected self-check errors made is increased due to the number of available resources. In total, backlog is detected at five intervals. With the flexibility of calling additional staff, the extent of rework is decreased by 25%.

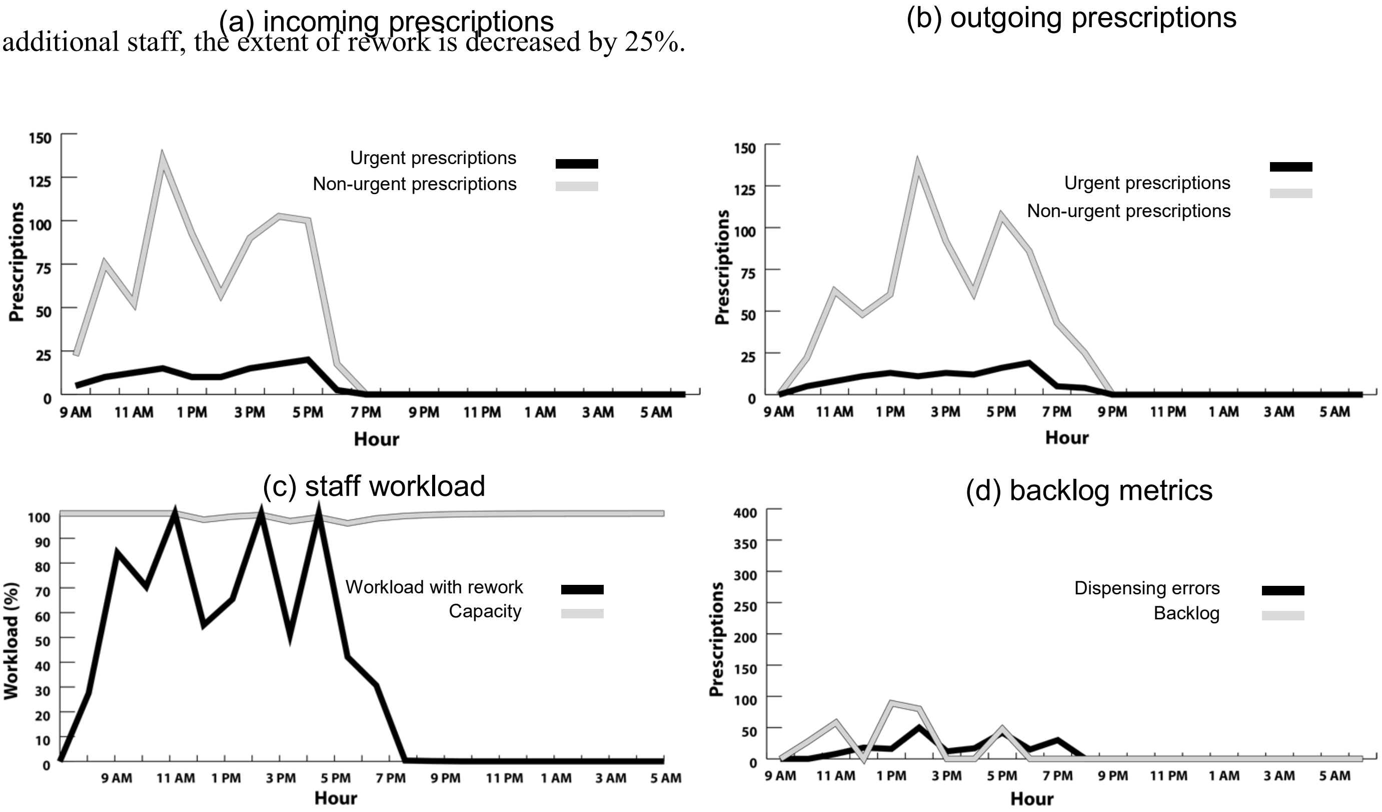

Figure 8. Results from Scenario 3 (dynamic staffing under winter pressure)

Table 3. Dynamic staff levels for workload in Scenario 3

Time (Hour)	9 AM	10 AM	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM	8 PM
Number of Labellers	5	5	5	5	5	17	9	5	15	7	7	5

3.4 Scenario 4: Equivalent-fixed staffing levels

The previous scenarios automatically incorporated delay when calling the required number of staff needed to reduce the backlog, and once backlog is reduced the model recalibrates the number of staff needed. The current scenario (Figure 9) applies a feasible approach by utilising the average number of staff needed to maintain the same results. In this scenario, output is steadied once eight labellers are used throughout the dispensing timeline (Figure 9). What does not change is the level of backlog, though variation is quite small, and no dispensing errors are made after 7 pm. In contrast to Scenario 3, which in total calls of up to 30 additional staff throughout the day are to combat any impending backlog, here prescription dispensing is completed 9 minutes earlier, and with a more stabilised workload throughout along with reduced rework and backlog. Furthermore, in Scenario 3 backlog was detected at five intervals, but here was detected at only three intervals. Here, the number of relabellings that labellers have to do based on incoming prescriptions was 18%, which suggests that having a fixed staff number throughout the day reduces the extent of rework.

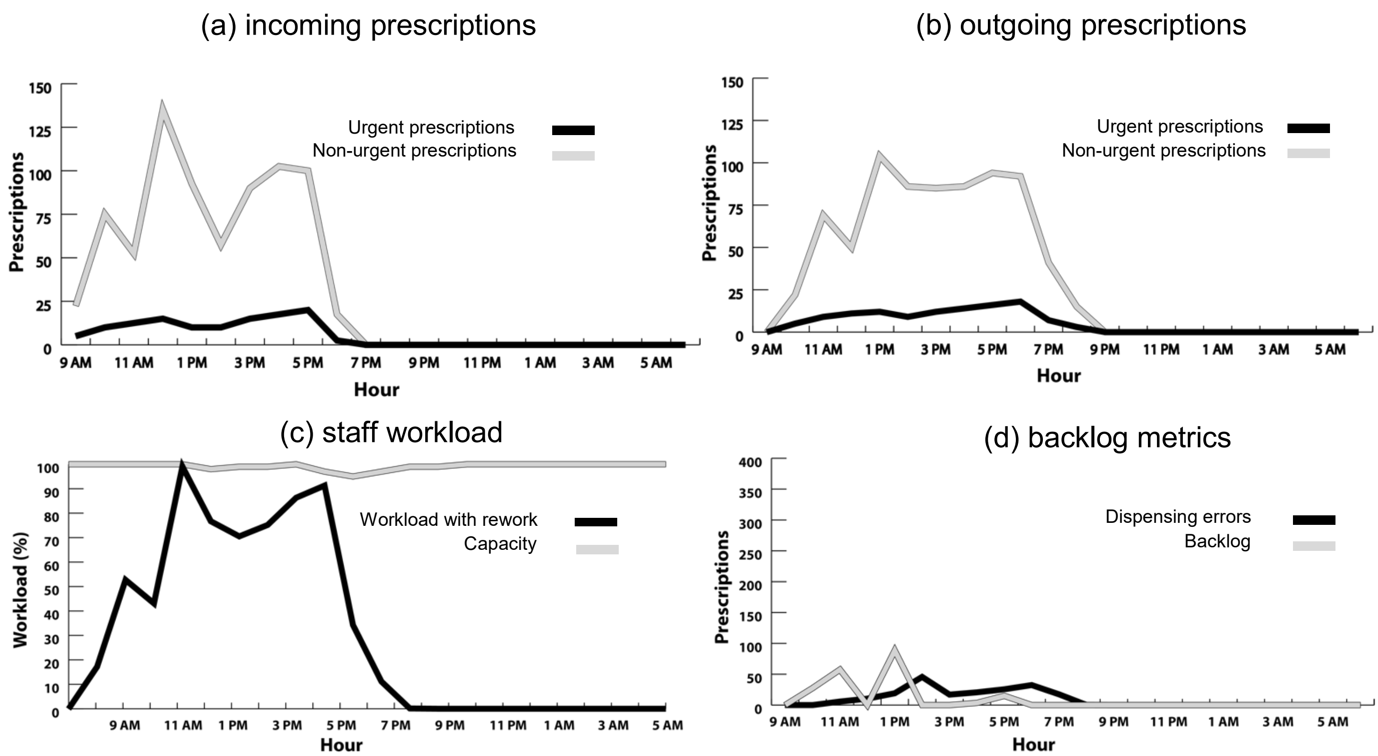

Figure 9. Results from Scenario 4 (fixed staffing equivalent to Scenario 3 under winter pressure)

4. Discussion

This study demonstrated how a quantitative SD simulation can be used to dynamically account for the mismatch between staffing level arrangement and demand on hospital pharmacies dispensing performance (backlog) and safety (error). Findings from the four different staffing arrangement scenarios are summarised in Table 4. These results reveal that a flexible staffing level arrangement, which dynamically adjusts the number of staff to demand variability during winter pressure, is less effective in reducing the amount of rework than maintaining an equivalent-fixed

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staffing level. This study is the first attempt to account for the unintended dynamics of rework due to dispensing errors, which is often missing from the linear model-based approach. This potentially negative and unintended dynamics of inadequate staffing levels make it more challenging to deal with demand variability (winter pressure). Our work demonstrates that SD modelling and simulation can provide a representation of reality that is sufficiently realistic to provide lessons to healthcare managers in the hospital pharmacy dispensary. Conscious efforts were made during the modelling process to include only necessary and sufficient components to create a realistic (useful) and insightful (ease of understanding) model, as suggested by Sterman (2004).

Table 4. Quantitative output of each of the scenarios

Scenario	Incoming urgent prescriptions	Incoming regular prescriptions	Staff	Time finished	Highest backlog (unlabelled prescriptions)	Errors detected and reworked
Scenario 1 - five fixed staffing under normal operation	47	298	5 labellers	8:01 PM	35	42
Scenario 2 - five fixed staffing under winter pressure	118	723	5 labellers	01:02 AM	219	309
Scenario 3 - dynamic staffing under winter pressure	118	723	5 – 17 labellers	8:17 PM	89	209
Scenario 4 – fixed staffing (equivalent to Scenario 3) under winter pressure	118	723	8 labellers	8:08 PM	88	153

Scenarios 1 (normal operation) and 2 (winter pressures) show how using the minimum number of staff with an increase in incoming prescriptions can have a detrimental effect on workload, dispensing errors, backlog, and finishing time. In Scenario 2, for example, using the standard five labellers to combat winter pressure forces labellers to finish around 1 AM, which is not sustainable. Scenario 3 (flexible staffing level arrangement under winter pressures), shows that labellers, the number of which is dynamically adjusted to the amount of the backlog, tend to maintain high workload that ultimately has a detrimental effect on their total capacity. When the extra staff joined, there is an increase in the number of labelling errors detected, thereby leading to an increase in the amount of rework to be done. Scenario 3 shows that this influences the backlog, and the number of additional staff needed to reduce the workload. By introducing a fixed staffing level (equivalent to the average staff number of Scenario 3) throughout the day, Scenario 4 shows that staff are not working to the maximum capacity consistently, so they make fewer dispensing errors and rework, and are able to complete their work slightly earlier than in Scenario 3.

Constant high workload can be considered more productive initially but has the effect of reducing capacity and self-checking once it persists in the long run. This causes the overall capacity of the staff to be reduced, signalling backlog and increased dispensing errors. Furthermore, it creates a bottle-neck between the workflow of labellers and checkers, thereby reducing the number of outgoing prescriptions. Our findings indicate that having an equivalent-fixed staffing level of eight labellers, as opposed to a dynamic staffing level whereby additional staff are called to reduce growing backlog, has a significant positive effect on the amount of rework generated. In Scenario 3, 25% of incoming prescriptions throughout the day are relabelled, whereas in Scenario 4 it was only 18%. This is a notable reduction of 7%, contributing to the efficiency of the dispensing process.

Our qualitative SD model (Figure 3) that we overlaid on the SEIPS model (Holden et al., 2013), and the corresponding quantitative SD model, demonstrate how structural/organisational characteristics of healthcare work systems, such as labellers' workload, can affect outcomes such as backlog and dispensing errors. Furthermore, our simulation illustrates that even when pharmacy managers respond with an adequate amount of resources, response delay can have an important impact on the way they can deal with demand variability. When adding and reducing additional staff to decrease a growing backlog, the pharmacy managers take an event-oriented perspective which is alluringly simple and often myopic. Once a backlog is detected, excessive or insufficient additional staff is brought in to counteract the growing backlog, without accounting for the current level of workload, the total capacity of the staff, the rate of incoming prescriptions, or the delay involved. This often results in the backlog growing drastically as an insufficient number of staff is brought in or having too many additional staff thereby wasting valuable resources. Finally, the concept of delay and lag needs to be taken into account when calling for additional staff or reducing the staffing levels once a backlog is increased. The hospital pharmacy dispensary involved in this study operates with the minimum staff required for the dispensary to function. As a result, they have to rely on ward-labellers, who are scattered across the hospital, to be called in when backlog is detected. By understanding how

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delay places a determinable role in backlog management and staffing levels, decision-makers can proactively analyse the level of delay involved in adding/reducing additional resources.

Understanding the correlation between high workload, staff capacity, backlog, incoming prescriptions, errors, and delay can allow pharmacy managers to comprehend the outcomes of their choices better when calling for additional resources or determining the correct staffing levels. Dispensing backlog can be averted or substantially diminished using the correct number of staff, by considering the total staff capacity needed vis-à-vis the current workload. Furthermore, it is critical for decision-makers to understand the delay involved between releasing and recalling extra staff to counteract growing backlog. Premature release of extra staff and delayed calling of additional staff from wards can have a significant impact on backlog. Once backlog is significantly reduced, incorporating a two-hour window for the additional staff from wards to be still around the dispensary can prove to be useful combating the sudden resurgence of backlog.

Considering that we focused our modelling on the performance of the labellers within the dispensary system, the findings of this study may be limited to the task flow of labellers. Further studies should be undertaken by introducing the workflow of other interrelated staff, and additional subsections that provide a definite impact on the safety and productivity of the whole dispensary systems. This includes the types of prescriptions, (automatic) robots, labellers, and nurses on the wards, and the role of clinical checkers. Moreover, additional research needs to be conducted on different types of engagement with stakeholders and how to share the simulation results with them effectively and simply. Whilst the generic hospital pharmacy model we created captures the essential elements of reality common to most hospital pharmacy dispensaries; it is an abstract representation with inherent limitations in replicating observed behaviour across other healthcare services. Though not universally applicable, the model can be extended to another pharmacy and other healthcare services where the differences in variables are minimal, and thus could benefit from the findings of this study. Such extensions include pathology labs and aseptic dispensing units where staffing level needs to be managed in response to varying demand, and safety-efficiency trade-offs are inevitable.

5. Conclusions

Our results demonstrate that system dynamics can provide practical insights into staffing level management in a hospital pharmacy, taking into account dynamic factors causing dispensing backlog and errors, and presenting decision-makers a holistic understanding of elements affecting system safety and performance. The current SD application allows pharmacy managers to test the impact of organisational decisions impacting safety and productivity, including the effects of changing assumptions. It is hardly possible to test a range of assumptions in real life, as the required time periods are prohibitively long. It is also very risky, since the consequences of bad assumptions and decisions could be disastrous. The power of the SD approach is to allow assumptions, some of which may be purely speculative but potentially useful, to be tested in a matter of seconds. Findings from our scenario-based simulations revealed that a flexible staffing level arrangement, which dynamically adjusts the number of staff to demand variability during winter pressure, is less effective in reducing the amount of rework than maintaining an equivalent-fixed staffing level. This enhanced understanding of the correlation between high workload, staff capacity, backlog, incoming prescriptions, errors, and delay can allow staffing decision makers to comprehend the outcomes of their choices better when calling for additional resources or determining correct staffing levels.

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