Agents-based simulation and BLV diffusion coupling approach for nurses interruptions effect behavior in an emergency department

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***Abstract*—Interruptions in Emergency Departments (EDs) are frequent and can significantly degrade nurses' performance, increase fatigue, and negatively impact overall system performance. Nevertheless, some types of social interruptions may have beneficial effects. Understanding how interruptions spread and evaluating their impact at both individual and collective levels is essential. This study proposes an agent-based simulation model coupled with a Boltzmann-Lotka-Volterra diffusion approach to model and represent the emergent behaviors generated by interruptions. Several metrics are evaluated through computational experiments. The results highlight that interruptions not only increase individual fatigue but also show that certain social interruptions can be beneficial at the collective level. This study shows the pertinence of combining simulation and diffusion models to better understand human behavior in complex environments.**

Keywords*—Emergency department (EDs), nurses, interruptions, fatigue, Boltzmann-Lotka-Volterra (BLV)

I. Introduction

Hospitals today are facing a personnel pressure, this means the reduction in healthcare staff and an increase in demand. The proper management of the emergency departments (EDs) and its resources is essential in healthcare systems [1]. The ED often represents the first point of contact for patients entering the hospital. In EDs, nurses in particular, are required to care several patients simultaneously. It is necessary to work quickly, efficiently, while they are exposed to a high number of interruptions per hour. These interruptions can arise for various reasons, often come from communication with colleagues, providing information to patients or their families, or responding to unplanned requests from coworkers [2]. This phenomenon could reduce efficiency, increases time loss, and contribute to increase the cognitive workload among the staff.

Given the nature of healthcare activities, nurses in EDs experience a high workload, which is further exacerbated by frequent interruptions, unplanned tasks and contributing to chronic fatigue [3]. In general, interruptions have been observed to have a negative effect. They can reduce concentration, create confusion and increasing the time needed to complete treatment [4]. Nevertheless, some interruptions may also be perceived as protective, moderating cognitive workload. The objective of this paper is to model, through agents-based simulation and Boltzmann-Lotka-Volterra (BLV) diffusion coupling approach, the impact of interruptions in EDs and to evaluate their effects.

The remainder of the document is organized as follows. Section II corresponds to the related research. Section III describes the problem under study. The proposed framework is presented in Section IV. Section V is related to BLV and coupling. Collective analysis metrics are defined in Section VI. Computational experiments and results are presented in Section VII. Finally, Section VIII outlines the conclusion and perspectives.

II. Related Research

Koundal et al. (2024) [5] synthesize and examine the occurrence of interruptions and their potential adverse effects in work environments. Nurses are a population of particular interest, as it has been shown that there is a correlation between interruptions and cognitive workload. Several studies have focused on addressing the problem of interruptions in healthcare staff, identifying and quantifying their frequency during shifts.

The most of these studies are based on observational approaches. For instance, Chisholm et al. (2002) [6] used an observational, time-motion task-analysis approach across three different EDs. They found that the mean number of interruptions per 180 minute study period was 30.9 ± 9.7. Kwon et al. (2021) [4] adopt a descriptive survey using standardized observation tools determining a frequency of interruptions of 6.4 times per hour in the ED studied. Marsall et al. (2025) [7] through expert observations using a standardized assessment in an academic ED, determined that the staff were interrupted 7.7 times per hour.

Concerning to coupling of agent-based simulation and diffusion models, the review of Kiesling et al. (2012) [8] summarizes both theoretical aspects and applications to real problems. The author classifies social models into three levels: the micro-level, characterized by local pairwise communication links between agents;

the meso-level, which captures the collective influence of an agent's social environment; and the macro-level, representing global interactions at the societal scale, such as the influence of aggregate network-level opinion or macroeconomic factors. These approaches have been widely applied in domains such as agriculture, transport, and energy.

Applications of this approach in both health and healthcare contexts remain relatively limited. For instance, Loy and Tosin (2020) [9] employ it to develop a kinetic model for the spread of infectious diseases with quarantine measures. Furthermore, Dunn and Gallego (2010) [10] use this framework to analyze the diffusion of medical practices among clinicians through a network of healthcare facilities.

III. Problem Statement

The previous context highlights that interruptions constitute a relevant problem in healthcare systems, having been mainly studied through observational and qualitative approaches, and less frequently addressed using quantitative methods. We address the problem in a simplified ED scenario. The system consists of a set of nurses, one of whom is responsible for patient registration in the welcome-desk, while the remaining nurses (called clinical nurses) provide the healthcare services to patients. A set of patients arrives at the ED over time. When patients arrive, they are registered at the welcome-desk. After registration, they wait in a queue until a clinical nurse calls them for treatment. The assumptions are:

- Nurses are available at the beginning of the day.
- Patients with life-threatening conditions are attended to first. Otherwise, patients are served with a first-come, first-served rule.
- Each nurse can serve one patient at a given time.
- All healthcare treatment have the same duration
- Each healthcare treatment is execute in a rooms.
- Nurses are allowed one break per day.
- A break can start only if the nurse is not executing a treatment.
- Breaks are taken sequentially, no more than one nurse is on break at any given time.
- For all the nurses, the initial level of fatigue is zero.

IV. Propose Framework

A. Agent-base simulation

Due to the two main characteristics of agent-based simulation, including autonomy and interactions, this type of simulation is a suitable method for representing human collaboration, competition, and interactions in complex environments [11]. It allows to understand emergent collective behaviors.

The model includes three types of agents evolving on a discrete grid $\mathcal{G} = 0, \ldots, W-1 \times 0, \ldots, H-1$: patients $\mathcal{P}$, reception nurse $\mathcal{R}$, and clinical nurses $\mathcal{N} = n_1, \ldots, n_K$ and the time is discretized into steps. The agents are name: agent patients (**AP**), agent reception nurse (**ARN**), and agent clinical nurse (**ACN**).

Figure 1 shows how the agents interact in an emergency-type interruption. Being **ACN-2** the nurse source and **ACN-1** the nurse target of the interruption. *i)* An **AP** arrives and joins the welcome-desk queue, requesting to be registered. *ii)* If **ARN** is available and **AP** is at the top of the queue, it registers **AP**. *iii)* Once registered, **AP** waits in the queue for attention. *iv)* Being **ACN-1** available and **AP** prioritized, **ACN-1** takes **AP** for treatment. *v)* The **ACN-1** moves to a room to attend to **AP**. *vi)* **ACN-2** interrupts **ACN-1**. The mechanism triggering the interruption and the actions executed during it will be detailed later (Algorithm 1). *vii)* **ACN-1** temporarily pauses treatment and leave to assist **ACN-2**. *viii)* Once the interruption ends, **ACN-1** returns to the original room and continues treatment until completion. *ix)* **AP** leaves the ED if no additional treatments are required. *x)* **ACN-1** becomes available.

B. Fatigue Model

For each nurse n_i, we define at each time step t the fatigue $F_i(t)$ and its counter part the vitality $Z_i(t)$ such as:

$$F_i(t) = \begin{cases} 0 : \text{fully rested} \\ 1 : \text{fully fatigued} \end{cases} \tag{1a}$$

$$Z_i(t) = 1 - F_i(t) \tag{1b}$$

The workload is decomposed into two components with exponential memory:

$$D_i^{\text{wk}}(t) = D_i^{\text{wk}}(t-1) \cdot e^{-\lambda_{\text{wk}}} + w \cdot \mathbf{1}[\text{busy}_i(t)] \tag{2}$$

$$D_i^{\text{int}}(t) = D_i^{\text{int}}(t-1) \cdot e^{-\lambda_{\text{int}}} + D^{\text{int}}(t) \tag{3}$$

$$D_i(t) = D_i^{\text{wk}}(t) + D_i^{\text{int}}(t) \tag{4}$$

where w represents the workload per step, λ_{wk} is the physiological degradation rate, λ_{int} is the cognitive degradation rate, and $D^{\text{int}}(t)$ denotes the impact of interruptions received at time step t (defined in subsection V).

According with the literature on work fatigue [12] [13], fatigue accumulation and recovery follow exponential models in exclusive regimes. Based on these considerations, the following regimes are defined hereafter.

a) Work Regime: ($\text{busy}_i(t) = \text{True}$), exponential accumulation :

$$F_i(t) = 1 - \big(1 - F_i(t-1)\big) \cdot e^{-\gamma\, D_i(t)} \tag{5}$$

The interpretation is that the *reserve* $(1 - F_i)$ decreases exponentially under the effect of the load D_i. F_i rises rapidly at the beginning and then saturates near 1.

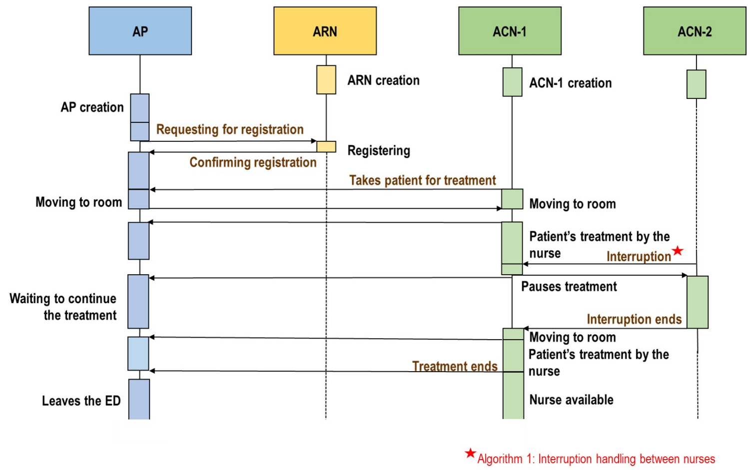

Figure 1. Agent Interaction Diagram

b) Pause mode: ($\text{pause}_i(t) = \text{True}$), rapid exponential recovery :

$$F_i(t) = F_i(t-1) \cdot e^{-\kappa_{\text{pause}}} \tag{6}$$

c) Idle mode: (neither in treatment nor on break), slow exponential recovery :

$$F_i(t) = F_i(t-1) \cdot e^{-\kappa_{\text{idle}}} \tag{7}$$

d) Social effect: (all states, see section V-A), support from a colleague reduces F_i regardless of the state :

$$F_i(t) = F_i(t) \cdot e^{-\kappa_{\text{social}}\,\beta_i(t)} \tag{8}$$

where $\beta_i(t) \geq 0$ is the recovery boost received at step t.

C. Healthcare treatment's time

The actual healthcare treatment's time depends on the nurse's stamina:

$$T_i^{\text{care}}(t) = \left\lceil T_{\text{base}} \cdot \big(1 + 0.5\,(1 - Z_i(t))\big) \right\rceil \tag{9}$$

A nurse with full vitality ($Z_i = 1$) performs the care in T_{base} steps; an exhausted nurse ($Z_i = 0$) takes $1.5 \cdot T_{\text{base}}$ steps. The additional time attributable to interruptions is:

$$\delta_i = T_i^{\text{actual}} - T_i^{\text{theoretical}} \tag{10}$$

Once the fatigue equations have been defined, we explain how this fatigue propagates between agents through BLV mechanism.

V. BLV AND COUPLING

In the BLV model [14], each component plays a significant role. First, we have to define a probability of interrupting a colleague nurse. This is described by the following relation

$$P_i(t) = P_{\text{base}} \cdot \big(1 + F_i(t)\big) \tag{11}$$

which fully integrates the fatigue of the nurse at step t. This Lotka term accounts for the fact that a tired nurse is more likely to interrupt a colleague, which in turn further tires the interrupted nurse, who is then more likely to interrupt a colleague. Collective fatigue evolves based on these interactions. Next, the Boltzmann component weights interactions based on the distance between individuals and their state (fatigue) following the relation for nurse n_i

$$W_{ij}(t) = Z_j^a(t) \cdot e^{-b \cdot c_{ij}(t)} \tag{12}$$

where $Z_j^a(t) = \exp(a \log Z_j(t))$ is the state of the target nurse, $c_{ij}(t)$ is the distance between nurse n_i and n_j and a (a_{blv}) and b (b_{blv}) are the model's sensitivity constants. Once the target has been selected, we must calculate the intensity of the exchange $Y_{ij}(t)$ between nurses. The formula used is a normalized form of the interaction energy which writes:

$$Y_{ij}(t) = W_i^T(t)^{-1} \cdot P_i(t) \cdot W_{ij}(t) \tag{13}$$

where $W_i^T(t)^{-1} = 1/\left(\sum_{j \neq i} W_i j(t)\right)$ is the normalization factor. It ensures that the impact is relative to the total number of interaction opportunities in the vicinity and factor $c(i,j)$ is the euclidean distance between nurse n_i and n_j. Thus, it is more natural to ask a colleague nurse for help when she is nearby. Finally, the Volterra term allows us to calibrate fatigue using a parameter from the exponential law. This term distinguishes physiological fatigue due to the work-day and from the cognitive ones. The progression of individual fatigue evolves at the rates dictated by this parameter. The impact of the interruption is reflected in the D^{int} component:

$$D^{\text{int}}(t) = \begin{cases} 0.2\ \Phi_{ij}(t) & \text{(source)} \\ 1.0\ \Phi_{ij}(t) & \text{(target)} \end{cases} \tag{14}$$

where

$$\Phi_{ij}(t) = Y_{ij}(t) \cdot \rho \tag{15}$$

with possible ρ values

- Social ($\rho = 0.5$): The impact is halved ("soft" interaction) with -1 step.
- Routine ($\rho = 1.0$): Nominal impact with $+1$ step.
- Emergency ($\rho = 2.0$): The impact is doubled (intense) with $+2$ steps.

The two different source/target ratio in (14) reflect the empirical asymmetry. The nurse who is interrupted experiences a much greater cognitive impact than the one who initiates the interruption. This value is then added to $D_i^{\text{int}}(t)$ with respect to (3). The BLV diffusion for modeling interruptions in agent-based simulation is then summarized by the following pseudo algorithm:

Algorithm 1 Interruption handling between nurses

Require: Source nurse i, set of nurses $\mathcal{N}$, parameters a_{blv}, b_{blv}

if i is not on break **and** P_i **then**
    for each $n \in \mathcal{N}/i$ **do**
        Compute c_{ij} ▷ the spatial distance (12)
        Compute W_n (12)
    end for
    Select target j at random in all $\{W_n\}$
    Compute interruption intensity Y_{ij} by (13)
    Compute impact of interruption by (14) and (15)
    Update D_i^{int} by adding D^{int} (14)
    if type $=$ *social* **then**
        Compute β_i and β_j as in (16) and (17) respectively
    end if
end if
Update the fatigue $F_i(t)$ with respect to the parameters.

A. Positive Effect of Social Interactions

For *social* interruptions, the target receives a recovery boost:

$$\beta_i(t) = 0.3 \cdot Y_{ij}(t) \quad \text{(source also benefits)} \tag{16}$$
$$\beta_j(t) = Y_{ij}(t) \quad \text{(target receives support)} \tag{17}$$

applied via equation (8).

B. Volterra component — memory and saturation

The persistence term $e^{-\lambda_{\text{int}}}$ in equation (3) introduces the long-term memory characteristic of Volterra equations: the cognitive stress of an interruption persists long after it has ended, and its effect accumulates non-linearly with subsequent interruptions. The saturation of F_i toward 1 in equation (5) corresponds to limit capacity, analogous to the carrying capacity in Lotka-Volterra models.

VI. Collective Analysis Metrics

To go a little bit over individual analysis, we propose in this work two indicators which can reflect the collective impact of interruptions-types.

A. Entropy of the interruption network

Shannon entropy quantifies the distribution of interruption flows:

$$E(t) = -\sum_{i \neq j} p_{ij}(t) \log_2 p_{ij}(t) \tag{18}$$

where p_{ij} is the proportion of the total energy flow directed from nurse n_i to nurse n_j :

$$p_{ij}(t) = \frac{\sum_t \Phi_{ij}(t)}{\sum_{k \neq l} \sum_t \Phi_{kl}(t)} \tag{19}$$

The normalized entropy is:

$$E_{\text{norm}}(t) = \frac{E(t)}{E_{\max}}, \quad E_{\max} = \log_2\big(N(N-1)\big) \tag{20}$$

for N nurses. $E_{\text{norm}} \to 1$ indicates that interruptions are uniformly distributed (homogeneous group with no dominant pair); $E_{\text{norm}} \to 0$ indicates a dominant structure.

B. Collective Hamiltonian

Inspired by the Ising model in statistical physics, the Hamiltonian $\mathcal{H}(t)$ captures the collective energy of the system such that:

$$\mathcal{H}(t) = \underbrace{\sum_i \frac{F_i(t)^2}{2}}_{\text{individual energy}} + \underbrace{\sum_{i \neq j} J_{ij} \cdot F_i(t) \cdot F_j(t)}_{\text{collective coupling}} \tag{21}$$

where the coupling J_{ij} is the normalized energy interruption flow :

$$J_{ij} = \frac{\sum_t \Phi_{ij}(t)}{\max_{k \neq l} \sum_t \Phi_{kl}(t)} \tag{22}$$

The coupling term $J_{ij} \cdot F_i(t) \cdot F_j(t)$ in (21) is maximized when two *extremely fatigued* nurses interfere with one another, this is the hallmark of collective amplification. For comparisons, we also consider the case where there is no interruption. In such a case, the Hamiltonian becomes $\mathcal{H}^{\text{cf}}(t)$ and is obtained by setting $J_{ij} = 0$ and $D_i(t) = D_i^{\text{wk}}(t)$, this leads to

$$\mathcal{H}^{\text{cf}}(t) = \sum_i \frac{F_i(t)^2}{2}. \tag{23}$$

The collective additional cost due to interruptions is therefore

$$\Delta\mathcal{H}(t) = \mathcal{H}(t) - \mathcal{H}^{\text{cf}}(t) \geq 0 \tag{24}$$

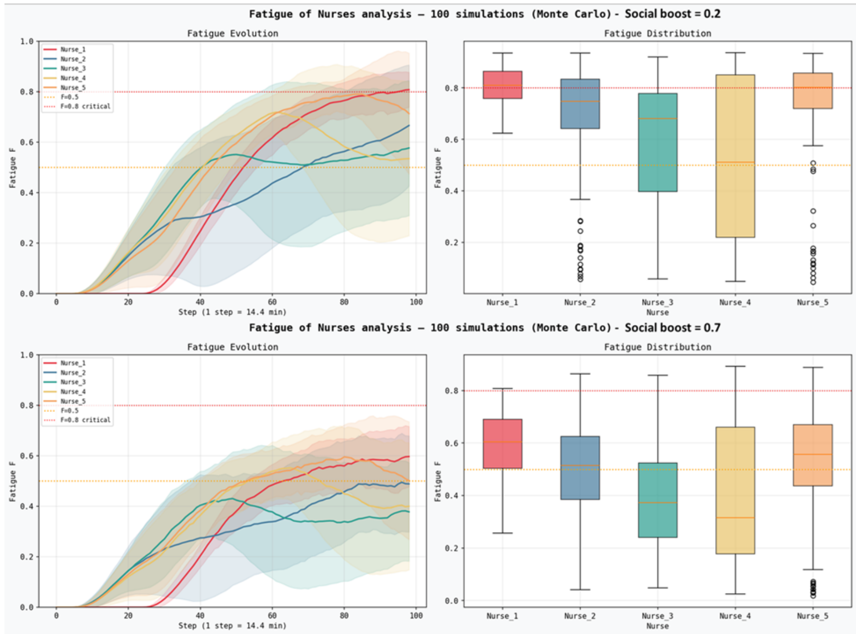

Figure 2. Nurses' Fatigue Evolution with Social Boost = 0.2 and 0.7

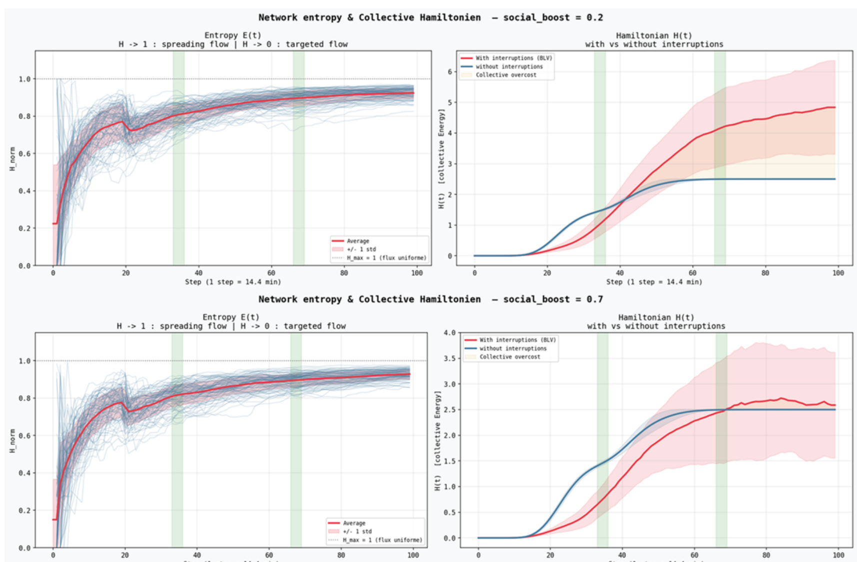

Figure 3. Network Entropy and Collective Hamiltonian with Social Boost = 0.2 and 0.7

VII. Computational Experiments and Results

A. Experimental setting

The agents-based simulation model was implemented in Python using the Mesa library [15]. The time discretized into steps $t \in 0, \ldots, T-1$, with $T = 100$ and $1, \text{step} = 14.4, \text{min}$, corresponding to a 24h day. One break represents 3 steps ($\approx 45\,\text{min}$). One reception nurse was considered and the number of clinical nurses was defined to be 5. The parameters used in the fatigue model are listed in Table I. To take into account of the stochastic variability, a Monte Carlo simulation was implemented. The results presented in the following section were obtained by generating 100 independent replications.

Table I. Fatigue model parameters

Accumulation rate	γ	0.010
Workload per step	w	0.28
Physiological degradation rate	λ_{wk}	0.07
Cognitive degradation rate	λ_{int}	0.03
Break recovery rate	κ_{pause}	0.13
Idle recovery rate	κ_{idle}	0.01
Social boost rate	κ_{social}	0.2; 0.7
Probability of interruption	P_{base}	0.3

B. *Analysis of results*

The results in Figure 2 show that accumulated fatigue increases in all cases for all the nurses, regardless of the level of social boost. This was to be expected, as one of the main causes of fatigue is the physical strain associated with undergoing medical treatment. Variations in accumulated fatigue levels at the end of the day may also be explained by the location of the break of each nurse. Furthermore, analysis of the box plots shows that, in the case of a social boost of 0.2, the medians are higher than those observed for a social boost of 0.7, despite the variability between the two scenarios.

Figure 3 show that the entropy curve is virtually the same for social boost = 0.2 and 0.7. It increase rapidly from 0 to $\approx$ 0.75–0.80 within the first 20 steps and then stabilizes around 0.90 until the end. The organizational structure of interactions does not depend on social support. It is determined by BLV dynamics and spatial proximity into the EDs.

The collective Hamiltonian $\mathcal{H}(t)$ evidences a difference between the scenarios. This is where the effect of social boost on collective behavior becomes apparent. With social boost = 0.2, $\mathcal{H}_{\text{red}}$ significantly exceeds $\mathcal{H}_{\text{blue}}$ starting around step 35. In contrast, for a social boost = 0.7, the phenomenon is contrarily. $\mathcal{H}_{\text{red}}$ is lower than $\mathcal{H}_{\text{blue}}$ throughout almost the entire simulation. The yellow collective overcost zone is virtually nonexistent. This leads to say that social interruptions appear to be beneficial for the collective when the social boost is over a threshold, to be characterized.

VIII. Conclusions and Perspectives

This study addresses the problem of nurse interruptions in EDs. We implemented an agent-based simulation model coupled with a BLV diffusion approach to represent the behaviors and impacts generated by interruptions. The computational results obtained from the experimental simulations show that interruptions increase the accumulated fatigue of all nurses. However, they also indicate that social interruptions can have a positive effect on the overall system performance when social boost is strong. This work is a preliminary study, and it aims to show the pertinence of using these type of hybrid modeling approach to address the problem of interruptions. Although the degradation of nurses at the individual level has a direct impact on system performance, the inclusion of collective metrics allows us to measure the overall collective effect on the system. In future, we aim to model an ED more realistic, based on a case study. Particular attention will be given to the evaluation of parameter values and to the modeling of cognitive workload.

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