Estimating horizontal movement performance of patient beds and the impact on emergency evacuation time

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ABSTRACT

Emergency evacuation of patients from a hospital can be challenging in the event of a fire. Most emergency evacuation studies are based on the assumption that pedestrians are ambulant and can egress by themselves. However, this is often not the case during emergency evacuations in healthcare facilities such as hospitals and nursing homes. To investigate emergency evacuations in such healthcare facilities, we performed a series of controlled experiments to study the dynamics of patient beds in horizontal movement. We considered a patient bed because it is one of the commonly used devices to transport patients within healthcare facilities. Through a series of controlled experiments, we examined the change of velocity in corner turning movements and speed reductions in multiple trips between both ends of a straight corridor. Based on the experimental results, we then developed a mathematical model of total evacuation time prediction for a patient bed horizontally moving in a healthcare facility. Factoring uncertainty in the horizontal movement, we produced the probability distribution of movement duration and estimated the probability that an evacuation can be safely performed within certain amount of time. In addition, we predicted that the evacuation time would be longer than the prediction results from an existing model which assumes constant movement speed. Our results from the model demonstrated good agreement with our experimental results.

1. Introduction

Pedestrian emergency evacuation has been one of the central topics in the field of fire safety engineering. In case of life threatening incidents such as fire and hazardous chemical spills, a well-prepared emergency evacuation plan can efficiently move occupants to the assembly points with minimum amount of time and ensure the safety of evacuees. Based on the degree of required aid during egress, occupants can be categorized into ambulant and non-ambulant occupants. Ambulant occupants can egress to the place of safety without help from other occupants. On the other hand, non-ambulant occupants need help when they move, especially in case of an emergency. The non-ambulant occupants can be further categorized into subcategories such as bedridden occupants and wheelchair users depending on the device that they are using.

Emergency evacuation of ambulant pedestrians has been investigated in experimental studies to understand pedestrian movement during emergency evacuations. Numerous experiments have been conducted in horizontal evacuation scenarios in which pedestrians egress within the same floor. For instance, researchers have studied evacuations through bottlenecks to understand the relationship between the bottleneck width and pedestrian flow, which is critical to the total evacuation time in room evacuations [1, 2, 3]. A considerable number of experiments have been performed to characterize pedestrian vertical movement through stairs such as downward moving speed and flow rate in a stairwell of a high-rise building [4] and the influence of stair slope on such pedestrian flow characteristics [5]. The pedestrian flow characteristics have been studied for harsh moving conditions including crawling in a room [6] and in a corridor [7], and the existence of earthquake-induced falling debris [8].

In most existing emergency evacuation studies, it is assumed that pedestrians are able to walk and egress by themselves. However, this is often not the case during emergency evacuations especially in healthcare facilities such as hospitals and nursing homes. Healthcare facilities accommodate considerable numbers of non-ambulant patients who have limited mobility and need the help of medical staff with evacuation devices during the evacuation process. To prepare emergency evacuation plans considering the non-ambulant pedestrians, it is necessary to understand the performance of evacuation devices such as their movement speed and movement dynamics.

Previous experimental studies of non-ambulant pedestrian evacuations analyzed video footage of the experiments to measure travel time between different reference points. By doing that, average movement speed was measured for different sections of an evacuation route such as a straight corridor and a stairwell. For example, Rubadiri et al. [9] performed a horizontal evacuation exercise of manual and electric wheelchair users. They measured the evacuation per-
formance index as a ratio of the wheelchair user movement speed without assistance to the movement speed of ambulant pedestrians. Based on the measured evacuation performance index, they predicted evacuation time of the wheelchair users and then compared it with the actual measurement of the wheelchair users. Strating [10] collected movement speed data of bedridden occupants in Dutch healthcare facilities. He reported an evacuation speed range from 0.54 to 1.34 m/s in Dutch hospitals and from 0.25 to 1.30 m/s in Dutch nursing homes. Hunt et al. [11] measured horizontal and vertical movement speed of evacuation devices including stretchers, evacuation chairs, carry chairs, and rescue sheets. They observed that the evacuation chair is the fastest among the tested evacuation devices with an average speed of 1.5 m/s in the horizontal evacuation and of 0.83 m/s in the vertical evacuation. Based on the measured movement speed of those evacuation devices, they also estimated the total evacuation time of non-ambulant patients in a high-rise hospital building. While those studies focused on measuring the average movement speed of non-ambulant pedestrian evacuation devices, change of velocity during the movement has not yet been studied in detail.

In pedestrian flow dynamics, it has been reported that pedestrians continuously moving with heavy load tend to have reduced movement speed due to fatigue [12]. Furthermore, several studies investigated speed profiles of pedestrians moving near obstacles in front of an exit [13], corners [14], and merging areas [15]. Such structural elements of pedestrian facilities often act as a constraint on the efficiency of pedestrian flow seemingly because pedestrians need to change their moving direction and speed.

Similar to the case of pedestrian flow dynamics, the movement of an evacuation device becomes slower when the device is moving in corners and areas of merging flow and interaction with other devices coming from different directions. In addition, there are often far more bedridden patients than medical staff in healthcare facilities. It is apparent that, in emergency evacuations, every medical staff needs to make multiple trips between the location of bedridden patients and the place of safety. One can expect that the medical staff experience some level of exhaustion when they evacuate all the bedridden patients and it is likely that their movement becomes slower as they travel longer distance. Such a slow-moving evacuation device affects the flow of subsequent evacuation devices and pedestrians, especially with limited passing opportunities in a narrow corridor. Consequently, understanding these non-linear dynamics of evacuation devices enables us to better estimate the evacuation performance of the devices with taking into account their speed profile and change of moving directions.

Among various evacuation devices, we considered the movement of a patient bed because it is one of the most commonly used devices to transport patients from one place to the another in healthcare facilities. In this study, we performed a series of controlled experiments to investigate the dynamics of patient beds in horizontal movement. Through the controlled experiments, we examined the change of velocity in corner turning movements and speed reductions in multiple trips between both ends of a straight corridor. Based on the experimental results, we then developed a movement duration prediction model and then applied the model for a patient bed horizontally moving in a healthcare facility. Incorporating uncertainty in the horizontal movement, we predicted probability that an evacuation can be safely performed within certain amount of time. The experiment setup and data collection methods are described in Section 2. As shown in Section 3, we analyze the dynamics of patient bed movement, develop a movement duration prediction model, and then apply the model for a patient bed horizontally moving in a healthcare facility. We summarizes the results with concluding remarks in Section 4.

2. Experiment setup

To collect patient bed movement data, we carried out a series of controlled experiments in September 2019 at the Singapore General Hospital, Singapore. In total, 4 males and 4 females aged between 25 to 35 without movement impairments took part in the experiments. In order to move a patient bed, the handlers were grouped into pairs of same gender handlers: male-male and female-female handlers. Additionally, one male (27 years old, 189 cm, 87 kg) was lying on the patient bed during its movement in order to substitute for a real non-ambulant patient. Before starting the experiment, the handlers had an orientation session and conducted a few warm-up trials to make them proficient enough in maneuvering the patient bed.

Figure 1 shows the sketches of the experiment setup: a right-angled corner and a straight corridor. In the right-angled corner setup, each handler pair was maneuvering a patient bed in the right-angled corner of 2 m × 2 m and two straight corridors of 2 m wide 5 m long. Handlers made right-turning movements by moving from the top to the right branches, and from the right to the top branches for left-turning movements. The handler pair repeated right and left turning movement at least 10 times. In the straight corridor experiment setup, each handler pair made 21 round trips with a patient bed in a straight corridor of 2 m wide 21 m long. By doing that, the handler pair moved the patient bed a distance of 882 m in effect. According to the usual practice [16], a pair of handlers was moving the patient bed together in both experiments. In each pair, one handler was acting as a leading handler who was guiding the movement direction of the bed, while the other handler was pushing the bed following the leading handler. Once the handlers reached the end of the experiment area, they changed their position in order to reverse their movement direction. The formation of handlers in each experiment setup is illustrated in Fig. 2.

Both experiments were recorded using cameras with a frame rate of 30 frames per second. The cameras were mounted on tripods which were set on the top of tables. In the right-angled corner setup, we set two cameras near the corner to closely observe the turning movement of the patient bed. In the straight corridor setup, two cameras were used to record
the bed movement from each end of the corridor. From video footage of the right-angled corner setup, we extracted patient bed movement trajectories using T-analyst, a semi-automatic trajectory extraction software developed from Lund University, Sweden [17]. The software has been applied in cyclist traffic safety analysis [18] and pedestrian flow analysis [19]. The conversion from video coordinates to the real world coordinates was performed by T-calibration, a calibration software accompanied by T-analyst. In T-calibration software, we placed calibration points and its real-world coordinates and then performed TSAI-calibration algorithm [20]. After the calibration process, we manually annotated pedestrian positions for every 10 frames on average in the video footage with T-analyst software. Next, T-analyst software then extracted pedestrian trajectories. Details of pedestrian trajectory extraction process can be found from T-analyst manual available from its webpage [17].

Table 1 shows the basic movement characteristics of handler groups in the turning movement experiment. We collected 10 to 15 trajectories from each handler group and in total \( N = 100 \) trajectories were collected. The distance traveled and the movement duration were measured for each trajectory in the area of \( x \leq 5 \) and \( y \leq 5 \) and then averaged for each handler group. The average speed was computed by di-
Table 1

Basic movement characteristics of handler groups in the corner area of \(x \leq 5\) and \(y \leq 5\).

| Handler groups | Gender | Movement direction | Orientation (rad) | No. of trajectories | Distance (m) | Duration (s) | Average speed (m/s) | Entering speed (m/s) |
|----------------|--------|-------------------|------------------|--------------------|-------------|-------------|---------------------|---------------------|
| LT_1           | Female | Left turn         | 1.57             | 0                  | 7.59 ± 0.16 | 10.59 ± 0.57 | 0.72 ± 0.03          | 0.80 ± 0.06          |
| LT_2           | Female | Left turn         | 1.57             | 0                  | 7.45 ± 0.11 | 9.05 ± 0.67 | 0.83 ± 0.06          | 0.87 ± 0.09          |
| LT_3           | Male   | Left turn         | 1.57             | 0                  | 7.58 ± 0.12 | 10.17 ± 0.73 | 0.75 ± 0.05          | 0.72 ± 0.15          |
| LT_4           | Male   | Left turn         | 1.57             | 0                  | 7.59 ± 0.10 | 7.34 ± 1.04 | 1.05 ± 0.11          | 0.95 ± 0.12          |
| RT_1           | Female | Right turn        | 3.14             | 1.57               | 7.67 ± 0.06 | 9.13 ± 0.54 | 0.84 ± 0.05          | 1.15 ± 0.07          |
| RT_2           | Female | Right turn        | 3.14             | 1.57               | 7.59 ± 0.10 | 7.24 ± 0.42 | 1.05 ± 0.06          | 1.32 ± 0.11          |
| RT_3           | Male   | Right turn        | 3.14             | 1.57               | 7.98 ± 0.12 | 9.33 ± 0.61 | 0.86 ± 0.04          | 1.05 ± 0.08          |
| RT_4           | Male   | Right turn        | 3.14             | 1.57               | 7.82 ± 0.13 | 6.47 ± 0.56 | 1.22 ± 0.08          | 1.51 ± 0.24          |
| Average        |        |                   |                  |                    | 7.65 ± 0.19 | 8.51 ± 1.57 | 0.93 ± 0.18          | 1.07 ± 0.29          |

Table 2

Basic movement characteristics of handler groups in straight corridor experiment.

| Handler groups | Gender | speed (m/s) | min. | max. | average |
|----------------|--------|-------------|------|------|---------|
| Group_1        | Female | 0.94        | 1.20 | 1.03 |         |
| Group_2        | Female | 1.34        | 1.64 | 1.47 |         |
| Group_3        | Male   | 0.98        | 1.13 | 1.04 |         |
| Group_4        | Male   | 1.31        | 1.70 | 1.53 |         |

Providing the distance traveled by the movement duration. The entering speed was measured when the patient bed is entering the area of \(x \leq 5\) and \(y \leq 5\). Handler groups RT_2 and RT_4 showed shorter movement duration than other handler groups seemingly because they entered the corner with higher entering speed and experienced smaller speed drop in the course of their movement.

In the straight corridor setup, based on the study of Luo et al. [12], we assumed that the fatigue experienced by the handlers is affected by the distance they transported the patient bed. The handlers were making multiple trips between one end to the other end of the corridor. We measured the time that the handlers took moving between the two ends of the corridor using the video footage. In doing that, we manually marked the transition period in which the handlers stopped and changed their position. After identifying the transition period, we obtained the travel time in each one-way trip and then calculated the average speed for each trip. The average speed was measured by dividing the distance traveled (882 m) by the total travel time that the handlers moving the patient bed. Table 2 summarizes the basic movement characteristics of handler group in the straight corridor experiment. Handler groups Group_2 and Group_4 showed higher speed but there is not significant difference between male and female.

3. Results and analysis

3.1. Turning movement

Figure 3 shows individual trajectories collected from the corner turning experiment setup. To understand the change of velocity in the course of turning movement, we firstly obtained the average path of all the handler groups moving in both movement directions. Similar to Hicheur et al. [21], we resampled the collected trajectories into \(N_f = 60\) equal intervals and then averaged the resampled trajectories for each rescaled time point \(\hat{t} \in [0, 1]\):

\[
x_{\text{avg}}(\hat{t}) = \frac{1}{N} \sum_{i=1}^{N} x_i(\hat{t}),
\]

\[
y_{\text{avg}}(\hat{t}) = \frac{1}{N} \sum_{i=1}^{N} y_i(\hat{t}).
\]

Here, \(N = 100\) is the number of collected trajectories from handler groups shown in Table 1. Likewise, we calculated trajectory deviation \(\sigma(i)\) to quantify the difference between the mean trajectory and an individual trajectory \(i\):

\[
\sigma_x(i) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i(\hat{t}) - x_{\text{avg}}(\hat{t}))^2},
\]

\[
\sigma_y(i) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i(\hat{t}) - y_{\text{avg}}(\hat{t}))^2}.
\]
\[
\sigma_y(\hat{t}) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i(\hat{t}) - y_{\text{avg}}(\hat{t}))^2},
\]
(3)

\[
\sigma(\hat{t}) = \sqrt{\sigma_x^2(\hat{t}) + \sigma_y^2(\hat{t})}.
\]
(4)

By making use of the rescaled time points, we identified start and end of turning movement. We measured the angular displacement \(\theta\) and its average \(\theta_{\text{avg}}\):

\[
\theta(\hat{t}_j) = \arccos \left( \frac{\vec{e}_0 \cdot \vec{e}_i}{\|\vec{e}_0\| \|\vec{e}_i\|} \right),
\]

\[
\theta_{\text{avg}}(\hat{t}_j) = \frac{1}{N} \sum_{i=1}^{N} \theta(\hat{t}_j),
\]
(5)

where \(\vec{e}_0\) is the initial moving direction which is set as \((0, -1)\) for left-turn movement and \((-1, 0)\) for right-turn movement. The moving direction at rescaled time \(\hat{t}\) is given as \(\vec{e}_j = (\Delta x / \Delta l, \Delta y / \Delta l).\) Here, \(\Delta x\) and \(\Delta y\) denote the difference between the values of \(x_i\) and \(y_i\) at the current rescaled time points \(\hat{t}_j\) and the previous rescaled time point \(\hat{t}_{j-1}.\) The displacement between the positions at rescaled time \(\hat{t}_j\) and \(\hat{t}_{j-1}\) is given as \(\Delta l = \sqrt{\Delta x^2 + \Delta y^2}.\)

Figure 4(a) presents angular displacement of the patient bed against rescaled time points. One can observe that the angular displacement curve is nearly straight between \(\hat{t} = 0.358\) and \(\hat{t} = 0.658\), indicating that the patient bed is turning with a constant angular speed \(0.24 \text{ rad/}\hat{t}.\) When the patient bed starts and ends the turning movement, either \(\sigma_x(\hat{t})\) or \(\sigma_y(\hat{t})\) is at peak value. Figures 4(b) and 4(c) indicate that the start and end of turning movement can be identified based on the components of trajectory deviation, i.e., \(\sigma_x(\hat{t})\) and \(\sigma_y(\hat{t}).\)

The identified locations of turning movement start and end are presented with the mean trajectory in Fig. 5. Similar to work of Dias et al. [22], it was observed that the turning movement started before and ended after Area 2 \((x \leq 2 \text{ and } y \leq 2)\).

Figure 6(a) shows examples of individual speed curves before resampling. Due to various initial speed and maneuvering duration, it is difficult to understand patterns in the speed curves. We applied the idea of the rescaled time points to such speed curves. We resampled the instantaneous speed \(v_i\) of individual handler groups into \(N_f\) equal intervals and then averaged the resampled speed for each rescaled time point \(\hat{t} \in [0, 1]:\)

\[
v_{\text{avg}}(\hat{t}) = \frac{1}{N} \sum_{i=1}^{N} v_i(\hat{t}).
\]
(6)

In order to compare different speed curves, we normalized the speed curves with entering speed \(v_0.\) Figure 6(b) presents the result of normalization performed against rescaled time \(\hat{t}\) for curves in Fig. 6(a). We performed normalization for

\[
N = 100 \text{ individual speed curves and then averaged their normalized speed in rescaled time space. Figure } 6(c) \text{ illustrates the average of normalized speed curves and its trend line. The trend line is generated by the normalized speed profile } \hat{v}(\hat{t}).
\]

According to minimum jerk principle (Hogan [23] and Pham et al. [24]), people tend to minimize jerk (i.e., a third-order derivative of position) while turning around a corner:
Figure 5: Average path (red solid line) with the locations of turning movement start and end (blue cross symbols).

Table 3
Normalized speed profile coefficients

| Coefficient | Value  |
|-------------|--------|
| $a_0$       | 1.0    |
| $a_1$       | 1.651  |
| $a_2$       | -10.08 |
| $a_3$       | 17.47  |
| $a_4$       | -8.56  |

\[
\int_0^1 \left[ \left( \frac{d^3 x}{d \hat{t}^3} \right)^2 + \left( \frac{d^3 y}{d \hat{t}^3} \right)^2 \right] d\hat{t},
\]

(7)

where $x$ and $y$ represent position in $x$- and $y$-axis at a rescaled time point $\hat{t}$. Based on the minimum jerk principle, the normalized speed profile $\hat{v}(\hat{t})$ can be represented by a fourth-order polynomial equation of rescaled time point $\hat{t}$:

\[
\hat{v}(\hat{t}) = a_0 + a_1 \hat{t} + a_2 \hat{t}^2 + a_3 \hat{t}^3 + a_4 \hat{t}^4.
\]

(8)

The coefficients $a_0$, $a_1$, $a_2$, $a_3$, and $a_4$ can be determined from the average of normalized speed curves in Fig. 6(c). Table 3 shows the coefficient values. Following the work of Dias et al. [25], we modeled the normalized speed profile $\hat{v}(\hat{t})$ with the same values in the start and end of the curve: $\hat{v}(0) = 1$ and $\hat{v}(1) = 1$.

### 3.2. Fatigue effect

We evaluated the fatigue effect in patient bed movement speed based on the speed reduction. The speed reduction was measured with respect to the initial movement speed $v_0$. According to the work of Luo et al. [12], the fatigue effect was reflected by the fatigue coefficient $f_a$:

\[
f_a = \frac{v_0 - v_i}{v_0}.
\]

(9)

Here, $v_i$ indicates the current speed which was calculated for each one-way trip from one end to the other end of the straight corridor (see Fig. 1(b)). Based on Eq. (9), we evaluated the fatigue coefficient $f_a$ for each handler group indicated in Table 2. Note that the current speed $v_i$ and fatigue coefficient $f_a$ are given as functions of distance traveled $s$, and $v_i$ is the average speed calculated from each one-way trip. Figure 7 shows the relationship between $f_a$ and $s$. One can observe that the fatigue coefficient values tend to rapidly increase in the beginning and then slowly grow.

We applied piecewise linear regression [26] to quantify
Table 4
The fatigue coefficients estimated by piecewise linear regression: the breakpoint and slopes.

| Coefficient | Value          |
|-------------|----------------|
| $s_x$       | 264.4 ± 24.7   |
| $\beta_1$   | $4.076 \times 10^{-4}$ |
| $\beta_2$   | $-3.492 \times 10^{-4}$ |
| $\beta_1 + \beta_2$ | $5.840 \times 10^{-5}$ |

Table 5
The slope coefficients estimated by piecewise linear quantile regression for 80% prediction band with quantiles 0.10 and 0.90.

| Coefficient | Quantiles          |
|-------------|--------------------|
| $\beta_1$   | $2.520 \times 10^{-4}$ | $5.476 \times 10^{-4}$ |
| $\beta_2$   | $-1.976 \times 10^{-4}$ | $-7.141 \times 10^{-4}$ |
| $\beta_1 + \beta_2$ | $5.447 \times 10^{-5}$ | $7.619 \times 10^{-5}$ |

Figure 7: Relationship between the fatigue coefficient $f_a$ and the distance traveled $s$. The measured fatigue coefficient $f_a$ from handler groups is denoted by blue circles (○). The corresponding trend line is indicated by red solid line. Black dashed line indicates the breakpoint location $s_x = 264.4$ m at which fatigue coefficient $f_a$ curve slope changes. Purple solid lines with cross symbols (×) show the boundaries of 80% prediction band with quantiles 0.10 and 0.90. The fatigue coefficient curve of Luo et al. [12] is denoted by green solid line with triangles (△). In their study, $f_a$ was measured for pedestrians carrying heavy items (10–20 kg) by hand.

3.3. Prediction of movement duration

Based on the average normalized speed curves shown in Fig. 6(c), we can predict the movement duration of a patient bed in the corner area (i.e., $x \leq 5$ and $y \leq 5$). We describe the distance traveled in the corner area $s_c$ with the following equation:

$$s_c = \sum_{i=1}^{N_i} v_i \Delta t_i$$

(11)

where $N_i$ is the number of intervals and $v_i$ is the speed at interval $i$. The interval length $\Delta t_i$ can be obtained by rearranging Eq. (11):

$$\Delta t_i = \frac{s_c}{\sum_{i=1}^{N_i} v_i}.$$ 

(12)

The movement duration $t_f$ is a summation of $\Delta t_i$:

$$t_f = \sum_{i=1}^{N_i} \Delta t_i$$

(13)

The speed at interval $i$ can be obtained from $\partial_t$ by multiplying entering speed $v_0$, i.e., $v_i = v_0 \partial_t$. Here, $\partial_t$ is normalized.
speed profile \( \hat{v} \) at interval \( i \). The movement duration \( t_f \) is given as:

\[
t_f = \frac{s_c N_i}{v_0 \sum_{i=1}^{N_i} \hat{v}_i}.
\] (14)

The average normalized speed profile \( \hat{v}_{avg} \) is given as:

\[
\hat{v}_{avg} = \frac{1}{N_i} \sum_{i=1}^{N_i} \hat{v}_i
\] (15)

and if we approximate Eq. (15) to continuous space by utilizing Eq. (8), \( \hat{v}_{avg} \) becomes

\[
\hat{v}_{avg} = \int_{0}^{1} \hat{v}_i \, d\hat{t}
\]
\[
= a_0 \hat{t} + \frac{1}{2} a_1 \hat{t}^2 + \frac{1}{3} a_2 \hat{t}^3 + \frac{1}{4} a_3 \hat{t}^4 + \frac{1}{5} a_4 \hat{t}^5 \bigg|_{0}^{1}
\]
\[
= \left( a_0 + \frac{1}{2} a_1 + \frac{1}{3} a_2 + \frac{1}{4} a_3 + \frac{1}{5} a_4 \right).
\] (16)

Accordingly, Eq. (14) should read

\[
t_f = \frac{s_c}{v_0 \hat{v}_{avg}}.
\] (17)

Here, distance traveled in the corner area \( s_c \), entering speed \( v_0 \), and average normalized speed profile \( \hat{v}_{avg} \) are input parameters. Based on Eq. (16), we can obtain \( \hat{v}_{avg} = 0.874 \).

In order to reflect the effect of fatigue on travel time, we considered the fatigue coefficient \( f_a \) and the relationship with the distance traveled \( s \) in the estimation of movement duration. Like Eq. (13), the movement duration \( t_f \) is given as

\[
t_f = \sum_{i=1}^{N_i} \Delta t_i,
\] (18)

where \( \Delta t_i \) is the travel time in segment \( i \) and \( N_i \) is the number of segments. Note that \( \Delta t_i \) is not constant here, meaning that the travel speed is different for each segment. The normalized speed \( \hat{v} \) is obtained after we rearranged Eq. (9),

\[
\hat{v} = \frac{v}{v_0} = 1 - f_a,
\] (19)

again, \( v_0 \) is entering speed. The average travel speed in segment \( i \) is given as

\[
\frac{\Delta s_i}{\Delta t_i} = \frac{v_{i-1} + v_i}{2},
\] (20)

where \( \Delta s_i \) is the distance traveled in segment \( i \) and \( v_{i-1} \) is the speed at the beginning point of segment \( i \) and \( v_i \) for the end point of segment \( i \). After combining Eqs. (19) and (20), we obtained the travel time of segment \( i \) as

\[
\Delta t_i = \frac{\Delta s_i}{v_0} \left( \frac{2}{\hat{v}_{i-1} + \hat{v}_i} \right).
\] (21)

3.4. Case study: Singapore General Hospital Emergency Department

In this case study, we demonstrate how the presented approach can be applied to predict the movement duration.
of a handler group transporting multiple bedridden patients. We selected the current Singapore General Hospital Emergency Department (SGH ED) for the case study. In Fig. 9, we present a schematic representation of the bedridden patient evacuation route in the current SGH ED. The evacuation route starts from the critical care unit (CCU) at (0, 0) to the place of safety (green triangle) at (45, 55). The evacuation route includes three straight corridor sections and two corner sections. The evacuation route is 2 m wide, same as the experiment condition.

Table 7
Bedridden patient evacuation route segments

| Segment type   | from       | to         | Length (m) |
|----------------|------------|------------|------------|
| 1 Straight corridor | (0, 0)    | (0, 11)    | 11         |
| 2 Corner       | (0, 11)   | (4, 15)    | 7.65 ± 0.19|
| 3 Straight corridor | (4, 15)   | (45, 19)   | 37         |
| 4 Corner       | (41, 15)  | (45, 19)   | 7.65 ± 0.19|
| 5 Straight corridor | (45, 19)  | (45, 55)   | 36         |

Figure 9: Schematic representation of bedridden patient evacuation route in current Singapore General Hospital Emergency Department (SGH ED). The evacuation route starts from the critical care unit (red square) which is placed at (0, 0) to the place of safety (green triangle) at (45, 55). The evacuation route includes three straight corridor sections and two corner sections. The evacuation route is 2 m wide, same as the experiment condition.

Figure 10: Numerical simulation results of movement duration for five round trips between CCU and the place of safety. The probability of finishing the movement within the reference time $T_{ref} = 999.09$ s is 23.6%. However, 76.4% of prediction results are longer than the reference time (indicated by the red shaded area), indicating that the reference time is not likely to be achievable. Here, the reference time $T_{ref}$ is computed with the traditional deterministic evaluation method using the mean value of input parameters.
is computed as $T_{ref} = M(t_p + t_q + t_l)$.  

$$T_{ref} = M(t_p + t_q + t_l),$$  

where $M$ is the number of round trips that the handler group makes and $t_l = 2l/v_0$ is the time required for the handler group to make a round trip between CCU and the place of safety excluding the time for preparation and positioning. As can be seen from Fig. 10, the probability that the handlers evacuate five bedridden patients within the reference time $T_{ref} = 999.09$ s is $23.6\%$ while $76.4\%$ of prediction results are longer than the reference time. It appears that the traditional deterministic evaluation method based on the mean value of input parameters underestimates the movement duration.

### 4. Conclusion

We performed a series of controlled experiments to study the dynamics of patient beds in horizontal movement. In our experiments, we examined the change of velocity in corner turning movements and speed reductions in multiple trips between both ends of a straight corridor. In the corner turning movements, we observed that the start and end of turning movement can be identified based on the trajectory deviation. We also quantified common patterns in different speed curves by means of the normalized speed profile with rescaled time. In the straight corridor experiment, we discovered experimental relationship between the fatigue coefficient and distance traveled $s \leq 882$ m. Based on the experiment results, we developed a movement duration prediction model and then applied the model for a patient bed horizontally moving in a healthcare facility. In order to reflect uncertainty in the horizontal movement, we introduced a probability distribution to the horizontal movement parameters like entering speed, preparation and positioning time, and fatigue coefficients. According to our case study results, one can estimate the probability that an evacuation can be safely performed within certain amount of time. In addition, it is highly probable that the horizontal movement duration would be longer than the prediction results from an existing model which assumes constant movement speed. The case study results demonstrated that our model has potential in predicting emergency evacuation time of patient beds in healthcare facilities.

This study presents the experiment results from four handler groups in left and right turning movements, and the straight corridor movements, respectively. The experiment data was collected from a small number of handlers and they are all young adults who are not professionally trained. In addition, the weight of the bedridden patient was fixed. The experiment results might be different for various age groups, bedridden patient weight, and handlers' proficiency in moving patient beds. The proposed experiment results can be generalized with larger number of handler groups having different conditions like age and proficiency.

As a first step to study the dynamics of patient bed movement in horizontal space, we focused on the case of a patient bed movement based on simple experiment setups. Further experimental studies need to be carried out in order to extend the presented model. In emergency evacuations in healthcare facilities, there are several dozens of patient beds to be transported to the place of safety by multiple handler groups. During the evacuations, several patient beds are likely to

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### Table 8

| parameters | mean    | sd      | min    | max      |
|------------|---------|---------|--------|----------|
| $s_c$      | 7.65    | 0.19    | 7.27   | 8.03     |
| $v_0$      | 1.07    | 0.29    | 0.49   | 1.65     |
| $t_p$      | 7.96    | 5.19    | 4.10   | 17.64    |
| $t_q$      | 6.25    | 2.60    | 2.54   | 10.25    |
| $s_c$      | 264.4   | 24.7    | 215.0  | 313.8    |
| $\beta_1$  | $4.076 \times 10^{-4}$ | $7.780 \times 10^{-5}$ | $2.520 \times 10^{-4}$ | $5.476 \times 10^{-4}$ |
| $\beta_2$  | $3.492 \times 10^{-4}$ | $7.580 \times 10^{-5}$ | $-4.714 \times 10^{-4}$ | $-1.976 \times 10^{-4}$ |
| $\beta_1 + \beta_2$ | $5.840 \times 10^{-5}$ | $8.895 \times 10^{-6}$ | $5.447 \times 10^{-5}$ | $7.619 \times 10^{-5}$ |

### Table 9

The estimated probability that the evacuation of five bedridden patients can be safely performed within certain amount of time.

| Probability | Available time (s) |
|-------------|--------------------|
| 10%         | 892.89             |
| 20%         | 973.72             |
| 30%         | 1041.17            |
| 40%         | 1109.65            |
| 50%         | 1181.31            |
| 60%         | 1266.27            |
| 70%         | 1368.30            |
| 80%         | 1506.48            |
| 90%         | 1773.08            |

The traditional deterministic evaluation method. As stated in Zhang et al. [28], the value of reference time was computed based on the mean value of input parameters: evacuation route length ($l = 99.3$ m), preparation time ($t_p = 7.96$ s), positioning time ($t_q = 6.25$ s), and entering speed ($v_0 = 1.07$ m/s). For a handler group making five round trips between CCU and the place of safety, the reference time $T_{ref}$ is computed as

$T_{ref} = M(t_p + t_q + t_l).$
move in the same evacuation route at the same time and the interactions among them might affect the movement speed. The examples of observable interactions include the distance between two moving patient beds and the acceleration and deceleration in their speed profile. Future studies can be also planned from the perspective of emergency evacuation simulations. Hunt et al. [29] pointed out that the movement of evacuation devices has not been appropriately considered in existing evacuation simulation models although the movement of such devices is critical for vulnerable patients. We are currently developing an evacuation simulation model that can incorporate our findings in patient bed movement dynamics to explicitly reflect their movement during the emergency evacuations in healthcare facilities. The evacuation simulation models can check potential conflict with other evacuees and geometric elements such as doors and corners, and predict the total evacuation time for the scenarios in which patient beds are fleeing with other evacuees. Another interesting extension of the presented study is to optimize the evacuation time of bedridden patients in healthcare facilities. The optimization study can be performed to design optimal evacuation routes and estimate the number of handlers for transporting patient beds to the place of safety.

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