Reducing search times and entropy in hospital emergency departments with real-time location systems

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ABSTRACT

Although the consequences of hospital ED crowding have been studied extensively, the causes of crowding are still not well understood. Throughput factors in ED crowding models are difficult to study in a controlled fashion in a dynamic environment where healthcare demand changes rapidly, and physical and human resources suddenly become limited. Opportunities for automated, simultaneous, and low-cost observation of the location and movement of multiple units, patients and staff have recently arisen with the introduction of small, non-intrusive real-time location systems (RTLS). One such RTLS deployment reported here has initiated renewed consideration of quality and industrial statistics as applied to healthcare operations management. Novel metrics for essential constructs of throughput factors in ED crowding such as efficiency and effectiveness are proposed. In particular, causality is explained in terms of understanding of each construct, modeled in terms of entropy, information, and order. Experimental demonstration is given of how labor reduction and the probability of patients, personnel and equipment meeting in terms of less uncertainty can be explained. These novel metrics are expected to facilitate monitoring of how an ED reacts to different levels of crowding, provide insight into crowding dynamics, help evaluate interventions to decrease crowding, and ultimately improve care.

KEYWORDS

Emergency department; healthcare management; patient flow; process improvement

1. Introduction

Summary

Objective: Tools are needed for understanding the causes and mitigating the effects of ED crowding: streamlining flows and resources, reducing waiting times, optimizing value-added time for patients and staff, as well as ultimately improving care when deploying a real-time location system (RTLS) in a hospital setting. Design: Analysis and modeling of flows and positions of tagged items visualized with the RTLS so that one knows directly where people and equipment are located. Setting: Emergency department (ED) of a university hospital receiving about 200 patients per day. Participants: Sample of ED personnel plus a number of individual spot-checks based on data collected 24/7 during the project. Main outcome measures: Search times. Evidence of dynamic association. Results: Among the effects of the RTLS deployment are evidence for a significant labor-saving reduction in time spent for staff searching for patients, personnel and equipment. Novel metrics based on entropy as a measure of information and order are presented when explaining this labor reduction in terms of less uncertainty. In further studies, a methodology to detect dynamic associations, such as whether a patient has encountered either personnel or equipment, is reported, including an appraisal of the role played by measurement uncertainty in determining the probability of dynamic association. Conclusions: The results of this feasibility study promise future improvements in ED organization and care, as well as in other complex and dynamic scenarios within healthcare, such as intensive, home and community care as well as transportation and logistics.

1.1. Background and survey of the field

The burden on emergency departments (ED) of Swedish hospitals has increased significantly in recent years (National Board of Health and Welfare (Socialstyrelsen, Stockholm) 2011; Säfwenberg, 2008; Olsson, 2010). This is part of an international trend (Harris & Sharma, 2010; Kellerma, 2006; Schull et al., 2002) where similar dramatic increases in the number of patients seeking urgent care have been reported (Pitts et al., 2012). Patients are older and sicker, and the demands for rapid investigation and treatment are increasing and leading to ED crowding (Morley et al., 2018).

Theoretical models of ED crowding based on input, throughput and output factors have been described...
previously (Asplin et al., 2003). Input, in terms of the number of patients arriving at an ED, depends on the healthcare system and local community conditions and is generally outside the control of the ED. Throughput focuses on processes within the ED where both physical and human resources as well as patient demand for care will affect ED crowding. Output relates to the process of discharging patients from the ED, either back to the community, another healthcare setting, or into the hospital (Richardson, 2006).

ED crowding lowers the quality of care and patient safety and increases mortality (Bernstein et al. 2009; Richardson, 2006; Sprivulis et al., 2006; Trzeciak & Rivers, 2003). ED crowding results in less time for nursing, medicines may be forgotten (Stokowski, 2010), and diagnostics and treatment, including pain relief, can be delayed (Olshaker & Rathlev, 2006; Trzeciak & Rivers, 2003). Even for the most urgently ill patients there are delays in treatment and prolonged stays at the hospital ((National Board of Health and Welfare (Socialstyrelsen, Stockholm), 2018). The number of unplanned return ED visits within 72 h increases (Miró et al., 1999), as does short-term mortality (Society for Academic Emergency Medicine, Emergency Department Crowding Task Force. 2009; Sun et al., 2013), because of ED overcrowding.

Although the consequences of ED crowding have been studied extensively, the causes of crowding are not well understood (Morley et al., 2018). A hospital ED is a dynamic environment where healthcare demand can change rapidly, and physical and human resources can suddenly become limited. This creates a setting where the throughput factors in ED crowding models will be difficult to study in a controlled fashion.

However, detailed observations of staff reactions to different levels of crowding would provide insight into crowding dynamics and help evaluate interventions to decrease crowding. Previously, such observations have been very resource intensive and difficult to undertake. With the introduction of small, non-intrusive real-time location systems (RTLS), opportunities are enabled for automated and simultaneous observation of multiple units, patients and staff at a low cost. An example of a previous study of RTLS deployment in a hospital ED by Castner and Suffoletto (2018) looked at the number of times a senior ED physician entered a patient room as a surrogate marker for a patient encounter using radio-frequency identification tags.

In the present example of quality and industrial statistics applied to healthcare operations management, novel metrics based on data made available by deployment of a new RTLS at our ED are proposed for essential quality-assurance constructs such as efficiency and effectiveness.

1.2. Deployment goals with RTLS

Real-time location systems such as deployed in this project (Section 2) enable flows and positions to be visualized as patterns on computer screens accessible over the Internet, providing direct information about where people and equipment are located, as well as facilitating further analysis and processing. Novel IT-based algorithms with an RTLS can be one important tool to handle ED overcrowding by visualizing the current system state and predicting future behavior, as recently demonstrated by Bengtsson et al. (2016).

Deployment of real-time location systems (RTLS) in hospital departments and other similar complex and dynamic scenarios is, however, not without its pitfalls, according to several previously published studies: many decisions about RTLS systems and their implementation are made ad hoc, without clear clinical goals, often without clear definition of who is responsible for tagging the objects, and without convincing motivation for tracking staff (Fisher & Monahan, 2012).

An initial study of the needs and clinical goals was therefore made early in the project, in dialogue with staff at various levels in the hospital organization. Among several
research questions and care goals identified when introducing a small, non-intrusive real-time location systems (RTLS), the present study focuses on explaining labor reduction and the probability of patients, personnel and equipment meeting in terms of less uncertainty.

1.3. Search times and entropy in ED and quality engineering

The emerging science of improvement in health care and the need to add a perspective from the industrial quality improvement movement have been described by Bergman et al. (2015). While some think that hospitals cannot and should not be compared with car factories, as commented by Does et al. (2015), healthcare operations management in the fields of quality and industrial statistics is "at least as important as medical science when striving for better hospital care."

Processes for quality assurance in healthcare services analogous to those of industrial production were introduced in 2012 in an “ISO 9000-like” European norm: EN 15224, 15224 (2012). In that standard, 11 quality characteristics of health care services were identified: appropriate, correct care; availability; continuity of care; effectiveness; efficiency; equity; evidence/knowledge-based care; patient-centred care including physical, psychological and social integrity; patient involvement; patient safety; timeliness/accessibility.

Several of these healthcare service quality characteristics can be targeted as metrics of the impact of RTLS deployment in the ED hospital environment. Recent examples of projects addressing healthcare operations management and quality-assurance include: (1) El-Banna (2013), who made a case study of patient discharge time improvement using a Six Sigma approach; and (2) the RTLS studies of Bengtsson et al. (2016), mentioned in Section 1.2.

In the context of ED crowding, important throughput factors include: "the cohesiveness of patient care teams, physical layout of the ED, nurse and physician staffing ratios, efficiency and use of diagnostic testing (e.g., laboratory, radiology), accessibility of medical information, quality of documentation and communications systems, and availability of timely specialty consultation" (Asplin et al., 2003). In the dynamic environment of a hospital ED, healthcare demand can change rapidly, suddenly limiting physical and human resources and making throughput factors in ED crowding models difficult to study in a controlled fashion.

The concept of entropy can provide valuable insight in complex and dynamic situations such as ED throughput (Pendrill et al. 2019). The amount of “useful information” in an organization (such as an ED in the present case) is analogous to the original entropy concept as a measure of "useful energy" in steam engines (Carnot, 1803).

A task will be easier if there is some degree of order; i.e., less entropy. The greater the degree of order in an organization (e.g., coherency in hospital), the smaller the entropy and the greater the ability to perform tasks. Additionally, both distortion and loss of information—that is, uncertainty—can be modeled in terms of increases in entropy (Weaver & Shannon, 1963); i.e., disorder.

There are many contemporary studies of entropy-related changes in organization performance, ranging from explaining organizational efficiency in terms of entropy-based measures of synergy (see the hospital queuing studies of Chen, Liang, et al., 2015), to recent neurological research, with a study of the entropy of interconnectedness amongst different regions of the brain (Yao et al., 2013). An entropy-based approach not only provides a descriptive presentation, but also allows explanation and prediction, particularly in dynamic and complex environments.

Novel metrics for essential quality-assurance constructs such as efficiency and effectiveness based on RTLS data and with explanatory variables such as entropy, measurement information and order will be presented. These entropy-based metrics will be shown experimentally to explain labor reduction and the probability of patients, personnel and equipment meeting in terms of more order and less uncertainty; for instance, as a result of an RTLS intervention. The entropy concept can provide support when interpreting detailed observations of staff reactions to different levels of crowding, insight into crowding dynamics and help evaluate interventions to decrease crowding.

Following this introduction and goal summary, the paper will now summarize the experiences so far of implementing the project RTLS system and meeting at least some of the goals mentioned. A technical description of the system (Section 2) is followed by measures of the effects of the RTLS deployment in terms of a labor-saving reduction in time spent for staff searching for patients, personnel and equipment (Section 3). In Section 4, a methodology to detect and interpret dynamic associations is presented. The paper concludes (Section 5) with a consideration of what the results of this feasibility study promise in terms of future improvements in ED organization and care, as well as in other complex and dynamic scenarios.

2. RTLS system

A new, real-time location system (RTLS) is deployed in this project for tagging equipment, patients and staff with the aim of providing healthcare tools to optimize flows and

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Table 1. Results of satisfaction survey of staff.

| Scale                          | Scale Scoring Rule | PSSUQ v3 Norms (Means and 99% Confidence Interval) |
|-------------------------------|--------------------|----------------------------------------------------|
| SysUSe (system quality)       | Average items 1–7  | 2.57 2.8 3.02 1.53                                |
| InfoQual (information quality)| Average items 8–11  | 2.79 3.02 3.24 2.36                                |
| InfoQual (interface quality)  | Average items 12–15| 2.28 2.49 2.71 1.71                                |
| Overall (overall quality)     | Average items 1–16 | 2.62 2.82 3.02 1.80 (lower is better)              |

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2. RTLS system

A new, real-time location system (RTLS) is deployed in this project for tagging equipment, patients and staff with the aim of providing healthcare tools to optimize flows and
resources, reduce crowding, increase value-added time for patients and staff as well as improve care in a university hospital ED receiving about 200 patients per day.

A focus in the project has been on making it easier for healthcare professionals to find equipment, patients, and staff in their daily work, on post-analysis and on optimization of equipment placement, for instance. RTLS development has been done in close dialogue with staff, which has helped increase system usability, focus on perceived problems and lowering the threshold for the RTLS service to be used. One example of a result from staff feedback was to install dedicated touch screens for the service to increase availability and easy access in the hospital ED.

Practically, patients, staff and equipment are provided with small radio transmitters in the form of bracelets or small “tags.” The tagged items are grouped into categories and the healthcare professionals can select a category and see on the map where all items of that type are located. Figure 1 illustrates the technology of the project RTLS.

Indoor positioning with the project RTLS relies on the tags continuously broadcasting their identity via low-energy Bluetooth. The positioning infrastructure is formed by a set of observer modules that receive the tag signals and communicate the RSS (received signal strength) results via a cloud-based service. In the cloud positioning engine, signal strength measured by several observers is combined and translated into position using “lateration,” where signal strength is a proxy for distance (in contrast to triangulation, where a position is instead calculated from directions or angles). The result is an easy-to-read map shown for the healthcare professionals on a web-based user interface.

Reuse of existing, rather than installing new Wi-Fi networks, is possible when allowing the wall-outlet mounted observers to communicate with the cloud. Analysis functions and integration with other systems are also obtained via a cloud-based service. A new position for a tag is typically calculated every 10 seconds but, if lower real-time performance is acceptable, updating times can be extended, thus reducing accumulated data loads. Positioning precision depends on how many observers are used, and typically a precision of a few meters can be achieved. To reduce maintenance, tags with up to seven years of battery life have been developed.

The staff user experience and satisfaction with the project RTLS were measured according to PSSUQ (Post Study System Usability Questionnaire) (Lewis, 1992; Sauro & Lewis, 2012) with very good results (Table 1). We used the PSSUQ v3 questionnaire to measure the user experience in four categories: systems, information, interfaces, and overall quality. The 16 questions are assessed on a rating scale scored from 1–7, with the end points: Strongly agree and Totally disagree. A lower result value is better.

3. Labor-saving reduction in time spent for staff searching for patients, personnel and equipment with RTLS implementation

In response to the goals (Section 1), the effects of implementation of the project RTLS (Section 2) at the ED in terms of making it easier for healthcare professionals to find equipment, patients and staff in their daily work were measured and explained as follows.

3.1. Personnel perception of effects of RTLS on search time

Surveys were conducted in which ED personnel responded to a number of questions covering perceptions of the effects of the RTLS implementation in this project in terms of various aspects of usability (efficiency, effectiveness and satisfaction) before and after RTLS deployment.

Typical responses from 25 members of the staff to questions about how much the time personnel spent each day searching for equipment had changed with RTLS implementation are shown in Figures 2(a) and 2(b). The median search time appears to be at least halved—from 12.5(6.5) minutes to 5.0(2.5) minutes—as a result of implementation of the project RTLS.

3.2. Explaining effects of RTLS on search time

An intervention, such as—in the present case—the implementation of an RTLS in an ED, is expected to increase the efficiency and effectiveness of the organization. We attempt in this section to explain the observed reduction in search times

Figure 2. Histograms of responses of personnel (sample size 25) to questions about how much time they typically spent each day searching for equipment (a) before and (b) after RTLS implementation. Occupancy (on the y-axis) indicates the number of personnel responding for each category (search time in minutes) on the x-axis. The vertical line on each figure indicates the median, and the double-ended horizontal arrow indicates the expanded uncertainty in the mean ($k = 2$) in each case.

\[^{1}\text{Number in brackets: expanded uncertainty in the mean ($k = 2$)}\]
for equipment (Section 3.1) in terms of a reduction in entropy (Section 1.3) to make tasks easier (Section 3.2.1), as well as making the organization more capable (Section 3.2.2).

3.2.1. Measurement uncertainty, entropy and task difficulty

Entropy is a measure of the amount of information. With less information, it will be more difficult to find entities (equipment, personnel or patients) in the hospital ED. Between full knowledge and complete ignorance, there will be intermediate scenarios where the locations of some of the entities will be at least partially known, where the probability (or likelihood) of finding an entity in a particular (category) location, \( c \), is denoted \( q_c \). This finite probability could be because the tagging system (Section 2) has limited accuracy (with spatial standard uncertainties of typically \( \pm 10 \text{ cm} \)), which might lead to incorrect room assignment; a second alternative is that staff may believe that objects can be expected to be located in certain rooms (e.g., by memory or by routine). In any case, the higher the entropy, the more difficult will be the task of finding equipment or persons.

In such cases of intermediate precision, measures of order and uncertainty can be formulated in terms of a PMF distribution\(^2\) of the \( q_c \)'s, where \( Q \) denotes the state of the system (e.g., ED), for which the amount of information can be expressed in turn as entropy, which for a total of \( C \) categories (locations in the present case) is expressed as (Weaver & Shannon, 1963):

\[
H(Q) = -\frac{1}{C} \sum_{c=1}^{C} q_c \cdot \log_c(q_c)
\]  
(1)

An attractive aspect of employing entropy to describe disorder and uncertainty and the associated difficulty of the task of finding equipment is that the \( q_c \)'s do not need to be probabilities, but can be other estimates, from possibility, belief or plausibility approaches, for instance (Helton et al., 2006).

In Figure 3, different levels of disorder and uncertainty in RTLS data from the hospital ED are exemplified. The results come from a simulation of the effects of limited RTLS resolution on location uncertainty for eight fever thermometers distributed (PMF on left) over several rooms at the ED (map on right). A range of resolution—(A) least resolution; (E) medium resolution; (G) highest resolution—is achieved by deliberately spoiling RTLS performance on this given occasion by zooming in or out on a RTLS computer screen display. The right column of Figure 3 shows a map of the ED for each different zoom level, while the corresponding occupancy PMF for each level is shown in the left column of Figure 3:

- Scenario (A) represents complete ignorance, where all that is known is that there are eight thermometers somewhere in the ED, but they are equally likely to be in any room \( q_c \), probabilities equal 1/M for each of the rooms, \( c \), and \( M \) objects somewhere in the ED).

- Scenario (G) represents complete knowledge, where the RTLS indicates exactly where each of the thermometers is located.

In this simulation, only RTLS resolution changes while the actual distribution of objects (fever thermometers) is fixed. In actual deployment of the RTLS system in the hospital ED, both factors—resolution and object distribution—can be expected to change in the dynamic environment of a hospital ED, reflecting rapid changes in healthcare demand. The aim of our methods is to provide metrics for the throughput factors in ED crowding models, which are otherwise difficult to study in a controlled fashion when physical and human resources are suddenly limited (Section 1).

A task, such as finding fever thermometers in the hospital ED, will be easier as the degree of disorder (entropy) reduces. A first estimate of the task difficulty, \( \delta = -[\ln(C) - \sum_{j=1}^{M} \ln(N_j)] \), could be made with Brillouin’s (1962) derivation from eq. 1 of the amount of information (entropy) in messages relevant here, which considers a number, \( C \), of categories (or cells) and a number, \( N_j \), \( j = 1, \ldots, M \) of symbols of \( M \) different types (Pendrill, 2019). For the present RTLS case, the categories denote the different rooms in the ED and the symbols represent the different entities (e.g., fever thermometers) being searched for. The task of finding a thermometer will be easier (lower entropy) if it does not matter which thermometer is to be found; i.e., if \( N \) is small.

Such a model of task difficulty would, however, not account for the extra effort needed to access an item at a greater distance. This is considered next.

3.2.1.1. Accessibility. In the case studied, two factors are important in modeling workload for the task of finding equipment: in any one case, there is (1) a particular distribution of objects to be found across the available rooms (Figure 3), set against (2) the fixed disposition of the rooms, which sets a level of challenge in terms of the distance and associated effort (“accessibility”) needed to fetch each object from one of the rooms.

In probabilistic terms (Sundling et al., 2013), the aggregate accessibility \( A_{ij} \) (eq. 3) for a person \( i \) making a complete “journey” \( j \) is

\[
A_{ij}^m = \prod_b \left[ 1 - q_{ib} \cdot \psi_i(d_{ib}) \right]
\]  
(2)

Overall accessibility is thus the product of the individual person’s perceived effort, \( \psi_i \), when facing each of a series of barriers, \( b \), that have to be overcome during the journey at a distance (or effort or cost) \( d_{ib} \), together with the probability, \( q_{ib} \), that a person, \( i \), will face that particular barrier (Church & Marston, 2003). In the present case, the “journey” is undertaken by ED staff searching for fever thermometers.

Beyond the probabilistic approach of eq. 1, task difficulty in terms of the time and effort expended by staff searching for equipment (Section 3.1) can be gauged in terms of the pragmatic entropy (Weinberger, 2002). This pragmatic entropy is estimated as follows: as is well known, risk is not only a measure of the probability, \( q_j \), of a risky event (such as fetching a thermometer in a particular ED room), but will also include a pragmatic measure
of the impact, \( D \), of an event when it occurs: that is, \( \text{Risk} = D \cdot q \). The degree of order in the actual distribution accounting for accessibility is then measured as the sum of the pragmatic entropy over the rooms:

\[
H_{\text{weighted}}(Q) = -\frac{1}{C} \sum_{c=1}^{C} D_c \cdot q_c \cdot \log(q_c)
\]  

(3)

The impact term \( D_c \) (which enters as the term \( \psi_i(d_h) \) in the general accessibility eq. 2) is calculated simply inequation (3) for a thermometer in room \( c \) as the distance from the origin (ED reception) to that room; and \( q_c \) is the probability of a thermometer being in room \( c \).

### 3.2.2. Entropy and efficiency in organizations

Apart from describing task difficulty (Section 3.2.1), the entropy concept can also be used to describe the ability of an organization to succeed with a task. Item response theory (Rasch, 1960) posits that the odds ratio of successfully (probability, \( P_{\text{success}} \)) performing a task is equal to the ratio of an organizational ability, \( h \), to a task difficulty, \( k \):

\[
\frac{P_{\text{success}}}{1 - P_{\text{success}}} = \frac{h}{k}
\]

In entropy terms:

\[
H(P, Q) = \theta - \delta = \log \left( \frac{P_{\text{success}}}{1 - P_{\text{success}}} \right)
\]  

(4)

where \( \theta = \log(h) \) is the organizational ability to perform a task of difficulty, \( \delta = \log(k) \), which changes the state of the system (e.g., ED) from \( P \) to \( Q \); e.g., finding ED fever thermometers.

An explanation of the ability, \( \theta \), of an organization (e.g., hospital) analogous to our explanation of task difficulty (Section 3.2.1) is in terms of an entropy term \( \theta = -\ln(G) \), where \( G \) is the number of "coherent connections" between different parts of the organization (Pendrill et al., 2019).

### 3.2.3. Entropy-based metrics of intervention impact

Not only can the status quo for task difficulty (Section 3.2.1) and organizational ability (Section 3.2.2)—for instance, in the current efficiency of an organization—be described with entropy, but also measures of the impact (Figure 4) of various interventions aimed at improving that efficiency by reducing entropy, and thus reducing task difficulty and increasing organizational ability.

Any decrease in task difficulty, \( \delta \)—such as achieved by tagging of equipment—can be calculated as a reduction in the (polytomous weighted) entropy on implementation of the new RTLS. Figure 4 shows how the entropy as an estimate of the level of difficulty in searching for equipment—in both its basic form (eq. 1) and weighted pragmatically with accessibility (eq. 3)—varies as the resolution of the project RTLS is varied between (A) least resolution; (E) medium resolution; (G) highest resolution. With the implementation of the new tagging system, the best that can be achieved is to know exactly where all of the \( M \) objects are (one still, of course, has the effort of fetching them), where \( q_c' \) is the "true" probability of a thermometer being in room \( c \).

Figure 4 shows how the entropy as an estimate of the level of difficulty in searching for equipment—in both its basic form (eq. 1) and weighted pragmatically with accessibility (eq. 3)—varies as the resolution of the project RTLS is varied between (A) least resolution; (E) medium resolution; (G) highest resolution. With the implementation of the new tagging system, the best that can be achieved is to know exactly where all of the \( M \) objects are (one still, of course, has the effort of fetching them), where \( q_c' \) is the "true" probability of a thermometer being in room \( c \).
suggesting some degree of correlation between task difficulty, entropy and search time, despite the preliminary nature of the data.

In general terms, how well a task is performed by an organization will be determined by the “distance” (Kullback & Leibler, 1951) $D_{KL}(Q,P)$, in entropy between the initial state ($P$) and final state ($Q$). Following intervention (e.g., implementation of a RTLS), the conditional entropy $H(Q|P)$ will be the difference between the pre-intervention entropy $H(P)$ of the task tackled and the reduction in (cross) entropy $H(Q,P)$ from the intervention:

$$D_{KL}(Q,P) = H(P) - H(Q,P) = H(Q|P) \quad (5)$$

The effect $H(Q,P)$ of an intervention such as the project RTLS is thus to improve task performance by decreasing entropy when going from state $P$ to state $Q$.

Item response (eq. 4) shows how task performance can be improved by reducing entropy with either an increase in organizational ability $\theta$ and/or a reduction in task difficulty $\delta$.

After intervention, the entropy $H(Q)$ is expected to be less than the entropy $H(P)$ prior to intervention. A reduction in entropy (RHS of eq. 5) arising from improved resolution with the RTLS intervention can be modeled as the entropy

$$H(Q,P) \sim \ln(\rho) = \ln(\sqrt{3} \cdot 2 \cdot u) \quad (6)$$

of a uniform distribution associated with the finite resolution, $\rho$, of the “instrument” (RTLS in the present case), where $u$ is the standard measurement uncertainty (Pendrill et al., 2019).

### 3.3. Changing search strategies with RTLS

Depending on how personnel search for equipment, there will of course be some variation in the modeled entropy and task difficulty. For instance, the model adopted earlier (Section 3.2.1) assumed that, on average, all staff start searching from a unique location, the origin (ED reception), while it is likely that search strategies will change with the added information proved by the RTLS.

As mentioned, personnel will of course not be totally ignorant of equipment location. Whether the relatively large spread in search times reported by personnel, and shown in Figure 2, is mostly due to tasks of different levels of difficulty or to differences in individual search strategies and personnel ability requires further analysis.

Figure 5 gives an example of data showing a shortening in the distances traveled by equipment (from typically 3.2 km down to 2 km) already achieved thanks to a relocation of the storage area, as suggested by the added insight provided in the project RTLS.

Visualization of RTLS data such as in Figure 5 shows how activities in different ED areas are grouped together as one entity. The thickness of the line from one location to other areas in such plots indicates how frequently the equipment has moved between these areas. This can further be summed up to calculate a total distance that the equipment has traveled. With this information, further insights can easily be drawn as, for example, about the optimal storage location for minimizing the walking distance for the staff and the level of usage of individual equipment. The latter can lead to less cost when getting rid of unused equipment or the necessity of additional equipment for those in constant use. The total effect of this relocation on the personnel is likely double since staff also need to go to the storage area first to collect the equipment and, after putting it back, they need to return.
These observations are in line with previous examples of the deployment of state-of-the-art localization systems in which instrumentation, personnel or patients are tagged in, say, the ED of a hospital, which can be found in the work of Fisher and Monahan (2012) and Christe et al. (2010). The effects of such interventions are measured not only in technical terms, such as RTLS localization accuracy or battery life, but also in terms of reducing unnecessary overinvestment in equipment and, perhaps most importantly, freeing resources so that personnel can dedicate more of their time to patient care instead of searching for lost equipment. There is also an extensive literature in which the maximum entropy principle is used when studying queuing systems in a number of applications (Chen et al., 2015). The effect of such interventions is measured not only in technical terms, such as RTLS localization accuracy or battery life, but also in terms of reducing unnecessary overinvestment in equipment and, perhaps most importantly, freeing resources so that personnel can dedicate more of their time to patient care instead of searching for lost equipment. There is also an extensive literature in which the maximum entropy principle is used when studying queuing systems in a number of applications (Chen et al., 2015).

The main positive immediate impact of making an ED more efficient with the introduction of an ICT tagging tool and RTLS is found here to be the reduction in time and effort spent by staff searching for equipment (Section 3.1), and in accord with the RTLS project goals (Section 1). An improvement in organizational ability, such as enabled by RTLS implementation of electronic tagging of equipment (work stage $j'$ for improved locating of, e.g., fever thermometers), could be correlated further with increased collaboration between the nursing staff organization (work stage $j$) as an example of improved synergy in the "roof of a house-of-quality" model of hospital organization (Chen, Liang, et al., 2015). More elaborate models to be developed in future studies will include some account of how entropy can describe how personnel are organized to perform their tasks.

Hopefully, in due course all of this will lead, in turn, to better care—for instance, an all-important shortening in queuing times for patients (Marmor et al., 2012)—although this has not yet been observed with the present data. The modeling of task difficulty and organization ability, described in Section 3.2 in terms of entropy, promises to facilitate explanations of improvements in efficiency.

4. Dynamic association

The need to locate simultaneously personnel, patients and equipment so that evidence can be provided of dynamic association—that is, encounters between more than one entity occurring at a specific place and time (Frisch et al., 2009)—is also included in our studies of the project RTLS to improve the quality of hospital ED care (Section 1). Dynamic association can be important in gauging how well care has been delivered, as well as tracing the spread of infection.

4.1. Probabilities of dynamic associations

Figure 6(a) shows how the probability, $P_{\text{success}}$, of successfully identifying an encounter between two entities—in the present example, a member of ED staff and an item of equipment (volume pump) tagged with the project RTLS—varies as a function of time on a particular day, as calculated with eq. 6. There are separate curves for the two components—latitude ($y$) and longitude ($x$)—of location. Because of measurement uncertainty [Section 3.2.1] in each location estimate provided by the project RTLS, this probability is not 100% or 0%, but rather varies continuously as the two entities approach or recede from each other.

An expression for the probability of identifying correctly an encounter between two adjacent entities at locations $x_1$ and $x_2$, (e.g., a person and an item of equipment) is given by the overlap of the two (assumed) normal distributions $N(x_1, u_1^2)$ and $N(x_2, u_2^2)$, where $u$ is the standard uncertainty and $k$ (normally = 2 for 95% confidence):

$$P_{\text{success}} = 1 - \alpha = 1 - \text{erfc} \left( \frac{|x_1 - x_2|}{k \cdot \sqrt{2(u_1^2 + u_2^2)}} \right)$$

$$= \frac{2}{\sqrt{\pi}} \int_{-\infty}^{\infty} e^{-\left( \frac{|x_1 - x_2|^2}{k^2(u_1^2 + u_2^2)} \right)} \cdot dx$$

(7)

where $\text{erfc}$ is the complementary error function.

The curves shown in Figure 6(a), calculated with eq. 7, are based on the RTLS measured location for the two components—latitude ($y$) and longitude ($x$)—as the two entities approach or recede from each other, shown in Figure 6(b).
In any one application, it will be a matter of agreement between the involved parties to decide what level of probability actually is considered as a minimum to indicate an encounter (perhaps together with an estimate of a reasonable duration over which an encounter should be expected to occur).

4.2. Entropy and dynamic associations

The concept of entropy, applied to search times in Section 3, can also be useful in describing dynamic association. Shannon entropy is a good summary measure in the “social physics” studies of Alshamsi et al. (2016), where diversity in social communication is high when all social contacts receive the same amount of interaction time and decreases with less distributional uniformity (as in eq. 1), when fewer social contacts receive more interaction time than other social contacts.

For the current study of dynamic associations as bilateral encounters between personnel, patients and equipment in the hospital ED, the same entropy-based formalism and concepts used in Section 3.2.3 may be invoked in the current RTLS studies. Task difficulty—that is, how easily two entities meet—will depend on the distance between them, obviously reducing as the distance reduces. This effect is captured by associating an entropy based on the probability of the dynamic association, as given by eq. 7, which in turn can be entered into the item response expression, eq. 4. Similarly, measurement uncertainty—due here to the limited resolution of the project RTLS system—will add to the overall entropy in a dynamic association, as may be calculated with equation 6.

5. Conclusion

We have proposed novel metrics, based on data made available by deployment of a new RTLS at our hospital ED, for essential constructs of throughput factors in ED crowding such as efficiency and effectiveness. In particular, causality is explained in terms of understanding of each construct, modeled in terms of entropy, information, and order:

- Overall performance has been modeled in terms of entropy when an organization of a certain ability tackles a task of a certain level of difficulty.
- The effects of RTLS implementation result in entropy reductions coupled to improved resolution and reduced uncertainties.

Explanations of labor reduction and the probability of patients, personnel and equipment meeting in terms of less uncertainty based on our new RTLS data are given:

- The observed reduction in equipment search times seems experimentally to match well the corresponding reduction in entropy and task difficulty in going from total ignorance to the level of knowledge provided by the RTLS.
- The probability of physical encounters in time and space via the dynamic association of pairs of tagged items—such as a tagged staff member meeting tagged equipment in a hospital environment—has also been calculated for actual RTLS observations.

This entropy-based approach to construct specification is particularly valuable in ED contexts where throughput factors are difficult to study in a controlled fashion in a dynamic environment where healthcare demand changes rapidly, and physical and human resources suddenly become limited. The novel metrics are expected to facilitate monitoring of how an ED reacts to different levels of crowding, provide insight into crowding dynamics, help evaluate interventions to decrease crowding, and ultimately improve care.

In addition to clear benefits shown in this work of RTLS implementation at an ED with respect to goals set out in Section 1, other RTLS goals remain to be examined, such as whether the degree of workload can be read from the patterns, together with the other goals formulated in the initial stages of the RTLS project. Follow-up studies, to add to the
robustness of the methodology, should include patient experience as well as investigations at other EDs.

The results of this feasibility study suggest that the use of RTLS will allow improvements in ED organization, transport, logistics and care, as well as in other complex and dynamic healthcare settings, such as intensive, home and community care.

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**Author contributions**

JWa: Responsible for the system and the technical design of the RTLS service from Sony that were used in TagOn; AE: continuous evaluation of the service from Sony that were used in TagOn; UP collaborated in the design and the execution of the research project; L.P: assisted in analyses, developing interviews and standardized testing; UB: initiated the project, built the consortium, applied for VINNOVA funds and led the project. All authors have taken part in writing of the manuscript and read and approved the final version.

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