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Comparison of Reverse Triage with National Early Warning Score, Sequential Organ Failure Assessment and Charlson Comorbidity Index to classify medical inpatients of an Italian II level hospital according to their resource's need.

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## **Abstract**

### Background:

Resource allocation in our overcrowded hospitals would require classification of inpatients according to the severity of illness, the evolving risk and the clinical complexity. Reverse triage (RT) is a method used in disasters to identify inpatients according to their use of hospital resources.

**The** aim of this observational prospective study is to evaluate the use of RT in medical inpatients of an Italian Hospital and to compare the RT score with National Early Warning Score, Sequential Organ Failure Assessment and Charlson Comorbidity Index.

Material and Methods: Cluster sampling was performed **on** High Dependency Unit (HDU), Geriatrics (Ger) and Internal Medicine (IM) wards. We calculate RT, NEWS, SOFA and CCI from inpatient charts. Length of stay (LOS), transfer to a higher level of care, death and discharge date were collected after 30 days.

### Results:

We obtained demographics, comorbidities, severity and clinical complexity of 260 inpatients. We highlighted differences in NEWS, SOFA and CCI in the three divisions. On the contrary RT score was **uniformly** high (median 7), with 85% of patients with RT=8. NEWS, SOFA **and CCI** were higher in patients with higher RT score.

We used the sum of the interventions listed by RT (RT sum) as a proxy of the level of care needed. RT-sum showed moderate correlation with NEWS ( $r=0,52$  Spearman,  $p<0,001$ ). RT-sum was the highest in HDU, related to the evolving severity of HDU patients. Ger patients, that showed the highest CCI score (with all patients in the  $CCI \geq 3$  category) had the second highest RT-sum.

### Conclusions:

RT score showed similar values in the majority of the inpatients regardless of differences in NEWS, SOFA and CCI in different ward subgroups. RT-sum is related both to evolving severity (NEWS) and to clinical complexity (CCI). RT and NEWS could predict inpatient level of care and resource need associated with CCI.

## **Introduction**

Predicting the outcome of serious illnesses and the individual resource need is increasingly important for the planning, management and assessment of interventions in the health-care system, as well as for its more traditional role in providing a prognosis for individual cases. Resource management at institutional level requires repeated assessment of health-care needs compared with resource availability to obtain an efficient and equitable resource allocation [1].

In an overcrowded hospital, appropriate management of inpatients disposition and resources would not only need frequent census of bed occupancy rates, but also a prognostic stratification based on severity, clinical risk and co-morbidity [2-3]. Different models have been proposed for clinical risk assessment: diagnosis, severity-of-illness, deterioration of physiological parameters and co-morbid conditions are used as risk adjusters to evaluate clinical complexity [4-5].

The severity-of-illness scores (Sequential Organ Failure Assessment SOFA etc. ) have been extensively studied in acute critical care patients to define the appropriate level of care and are known to correlate with mortality and length of stay (LOS)[6-8]. On the contrary, in Internal Medicine and in general wards severity scores are seldom used and were not previously validated universally, whereas many different prognostic scores exists for many different pathologies (i.e. pneumonia, cirrhosis, hematologic malignancies, oncology etc.) [9].

In the United Kingdom, the National Early Warning Score (NEWS) is universally used to monitor clinical risk and evolving illness severity; it guides monitoring, interventions and increased level of care both in the ED and in the general ward. NEWS weighs various physiological parameters by severity, combining clinical findings and measurements that nurses routinely observe. The results give a composite score, which reflects how unwell the patient is [10-15]. NEWS score has been shown to correlate with mortality and need for escalation of the intensity of care (transfer to intensive care unit (ICU) etc.) in studies of patients with cancer, sepsis and medical diagnoses [13-18].

Moreover, resource use and LOS depend on case complexity and co-morbidities. The Charlson Comorbidity Index (CCI) is the most extensively studied co-morbidity index [19,20]. It captures cogent co-morbidities with the main acute diagnosis, has a good prognostic value and is used to guide the clinical decision about treatment (surgery, chemotherapy etc).

Reverse triage (RT) is a method proposed by Kelen et al. to increase surge capacity during disasters [21-24], prioritizing for early discharge of patients whom need the least amount of medical assistance [25]. RT is a method for adult and paediatric inpatient disposition to reduce the negative outcomes associated with early discharge. Indeed RT selects patients having a small risk for serious complications not requiring major medical assistance for at least 96 h [25-31]. This classification is built on critical interventions and is suitable for evaluating the individual level of care and helpful in transport decisions. It was proposed to cope with the daily surge and to reduce crowding with a lower cut-off for risk tolerance with respect to disasters. [31-34]

To facilitate clinical decision-making processes in this setting it would be useful to develop a reverse triage system that includes the above-mentioned prognostic variables and other medical data to provide a real-time overview of inpatients' medical status and complexity.

The aim of the present observational prospective study is to evaluate the use of RT in the medical

inpatients of an Italian Hospital and to compare the RT score with evolving severity scores (NEWS), severity scores (SOFA) and comorbidity scores (CCI).

### **Materials and methods**

All adult patients admitted into the High Dependency Unit (HDU), Geriatrics (Ger) and Internal Medicine (IM) wards in a middle size (300 beds) suburban teaching hospital in Orbassano (Torino) were prospectively sampled and surveyed. From 16 October 2017 to 22 January 2018 we canvassed the patients of the 3 divisions every 4 days. We excluded patients admitted or discharged the day of the enrolment and patients who did not want to participate in the study or were not able to give informed consent.

If the patient accepted to be included and signed informed consent, the investigator examined the patient's chart to collect the demographic and clinical data and to calculate each score.

The investigator was blind about inpatient disposition; clinical decisions (procedures and disposition) were left to the ward's physicians not aware of the results of the scores.

Four days later, we canvassed the population again, enrolling only new patients, and so on. With this method, we canvassed each day of the week to avoid potential bias in inpatient disposition.

For each patient the data collected from chart review were basic demographic information, arrival date, enrolment date and discharge date, inpatient unit type, the source of admission (non-elective vs elective and transfer from another division or another hospital).

### **Instruments**

#### **Reverse triage score (RT)**

RT includes a list of 28 critical interventions, defined and weighted on a scale of 1 to 10, based on the risk of a consequential medical event (CME) after withdrawal [26-29]. The CME is defined as unexpected death, impairment, or reduction in function for which a critical intervention would be initiated. In our study at enrolment we examined the patients' chart looking for critical interventions executed in the last 24 h; when more than one critical intervention was present we considered the higher weighted to define the RT score (range 3 – 10). An RT  $\leq 3$  identifies patients that have a very low risk of CME (<4%) and thus could be eligible for discharge. The intermediate category RT 4-7 identifies patients who need to continue to use hospital resources as a CME is likely to occur if interventions are delayed (12-33%). The higher score RT 8-10 identifies patients who need continued highly skilled care or are too instable to transport (CME risk 60-92%).

The total sum of the interventions (RT sum) was used as a proxy to assess the level of care needed (range 0 – 174).

**National Early Warning Score (NEWS)** is composed of 6 categories (Temperature (°C), Heart rate (beats/min), Systolic BP (mmHg), Respiratory Rate (breaths/min), Oxygen Saturation (%), Supplemental oxygen, CNS response (AVPU)). Each category is graded 0–3. The final score is the sum of each category score. A score <3 characterizes a stable patient. A score of  $\geq 3$  triggers further monitoring and reassessment. Composite scores of greater than 5 (or 3 in any of the parameters) trigger an urgent medical review. A score of over 7 triggers a review by a critical care outreach

team or medical response team [10-18].

Sequential Organ Failure Assessment (SOFA) is a well-known score with 6 physiologic variables, weighted 0 to 4, added together to give a total ranging from 0 to 24. A value of 2 or more is an early predictor of organ damage [7-10].

Charlson Comorbidity Index (CCI) considers the following medical conditions : myocardial infarction, angina, cardiovascular disease, cerebrovascular disease, dementia, chronic obstructive pulmonary disease (COPD), connective tissue disease, gastrointestinal disease, slight or serious liver disease, diabetes mellitus complicated or not, stroke, kidney failure, cancer, leukaemia, lymphoma, secondary metastasis, AIDS. The score ranges from 1 to 6 for each item, and total score provides an index of severity. Previous studies further stratified patients in categories with CCI 0, 1–2 and  $\geq 3$  [19-20] **where the latter implies a high comorbid burden.**

### Follow up

The digital chart record and discharge summary were examined **for all the patients 30 days after enrolment.** We collected data about length of stay, date of discharge, death and transfer to a higher level of care (HDU from IM and Ger, Intensive Care Unit for all the three divisions) or to another hospital for specialist care.

Data were described using means and standard deviations for quantitative continuous variables, median and interquartile range (IQR) for discrete variables. Absolute frequencies and percentages were used to describe qualitative variables. Based on the lack of normality of the data assessed by Shapiro Wilk test, comparisons were made by Kruskal - Wallis or Anova test for continuous variables and for categorical variables by Chi-Square test or Fisher exact test when the hypotheses for conducting a Chi-square test were not satisfied. All tests were two-sided and a p-value of 0.05 was considered significant. Analyses were performed using SAS V9.2 and R version 3.4.2 [34]. Spearman correlation was calculated for RT on one hand, and NEWS, SOFA and CCI on the other.

The institutional review board approved the study. Data were collected, registered and analysed anonymously.

### Results

In the study period, we canvassed globally 23 different days of the week, enrolling 260 patients (81 in HDU, 79 in Ger and 100 in IM). All the patients were admitted by non-elective urgent admission, with the majority admitted from **the** Emergency Department, a few transferred from other divisions (details in table 1). For all the patients, data from the 4 instruments were collected completely. Table 1 shows demographic data of all the enrolled patients, their co-morbid conditions and their source of admission.

We examined separately and compared the patients from the three departments and we highlight a significant difference in Gers' patients that were older than the HDUs' patients. IM showed a greater

prevalence of cancer patients by comparison with Ger and HDU; the latter instead showed a higher prevalence of Chronic Obstructive Pulmonary Disease (COPD), obesity and pancreatitis. No significant difference in gender or other variables distribution was found between the three division's populations.

Length of stay (LOS) was significantly shorter in HDU, followed by IM and Ger with the longest LOS; the same trend was shown in the subgroup of the patients that were finally discharged.

Mortality rates were higher in Ger, followed by HDU and IM but the difference was not significant (details in table 2).

The median value of RT score (considered as the higher weighted critical intervention) was similar in the three divisions and in the whole population with RT score =  $7.2 \pm 2$  ( $7.2 \pm 2$  in HDU,  $7.5 \pm 1$  in Ger,  $7 \pm 2$  in IM, *NS*). The majority (85%) of patients were in the RT=8 category. Table 3 shows the percentage of patients within the different categories of RT, no significant differences were found in the distribution of RT scores between the three divisions.

When considered as a sum of different critical interventions, RT sum mean ( $\pm$ SD) was  $14.7 \pm 7$  in the whole population. When examined in the three divisions RT sum was the highest in HDU ( $16.4 \pm 8$ ) patients, then decreased in Ger and in IM ( $14.2 \pm 5$  and  $13.8 \pm 8$  respectively), but the trend did not reach statistical significance.

NEWS was the highest in HDU ( $1.9 \pm 1$ ), by comparison with  $1.3 \pm 1$  in IM and  $1 \pm 1$  in Ger and the trend was significant ( $p < 0.001$ ); similarly, the proportion of patients with NEWS  $\geq 3$  and  $\geq 4$  was significantly higher in HDU than in IM and in Ger. Moreover, oxygen saturation was the most altered of the physiological NEWS parameters with a significant difference of prevalence in severe desaturation in HDU patients compared with the other divisions. Mean SOFA score was higher ( $1.9 \pm 2$ ) in HDU patients, with 52% of patients with SOFA  $\geq 2$ , in comparison with IM ( $1.6 \pm 1$ ; 43% SOFA  $\geq 2$ ) and with Ger ( $1.5 \pm 1$ ; 37% SOFA  $\geq 2$ ), but this trend did not reach statistical significance.

Comorbidity score CCI, on the contrary, was the highest in Ger patients ( $7.1 \pm 2$ ), intermediate in IM ( $6.7 \pm 3$ ) and was the lowest in HDU patients ( $5.6 \pm 3$ ); all the Geriatric patients were in the higher CCI category (CCI  $\geq 3$ ) versus the 89% in IM and 83% in HDU respectively.

More details are available in table 4.

Table 5 shows the results of NEWS, SOFA and CCI in patients classified according to RT categories of risk. As described above RT  $\leq 3$  identifies patients at very low risk of CME after withdrawal of interventions, RT from 4 to 7 identifies patients at moderate risk of CME after withdrawal of interventions, RT from 8 to 10 identifies patients at high risk of CME after withdrawal of interventions. NEWS, SOFA and CCI scored lower in the low risk RT category and higher in the high risk RT category. This common ascending trend was significant for all three tools, showing concordance between the four instruments.

Table 6 shows the outcomes of the study in patients classified in low and high risk using the above-defined cut-off of each score. The subgroup of patients with a RT  $\leq 3$  showed a significantly shorter total LOS and were discharged significantly earlier (5.7 days after assessment) by comparison with the subgroup of patients with RT  $> 3$  (13 days after assessment). Similarly patients with a higher CCI

were discharged later and had a longer LOS by comparison with patients with a CCI<3. We observed that patients with NEWS<3 had a similar, but not significant, trend toward shorter LOS and early discharge compared with patients in the NEWS≥3 group. The patients grouped by SOFA did not show significant differences in their LOS and in the timing of discharge after assessment. Conversely mortality rate was higher in patients in the group with possible organ damage, classified by a SOFA ≥2, by comparison with the group with SOFA <2.

Figure 1 shows Spearman correlation between RT and NEWS, SOFA and CCI scores respectively. There was a fairly good correlation between RT sum and NEWS (r 0.52, p < 0.001); a moderate correlation was found between RT sum and SOFA and CCI respectively.

## **Discussion**

The main objective of the study was to compare RT, a stratification system of inpatients by the level of care and the need of resources, with other prognostic scores more diffusely used to evaluate risk of physiological deterioration (NEWS), severity of organ damage (SOFA) and clinical complexity (CCI). We aimed to evaluate if these four tools were able to describe the actual differences in intensity of care in our “real life” inpatient cohort. Our population was admitted into three different wards: two normal wards with different characteristics (geriatrics and internal medicine wards) and the High Dependency Unit (HDU) where patients can be cared for more extensively than in a normal ward, but not to the point of intensive care. Patients may be admitted to a HDU bed because they are at risk of requiring intensive care admission or as a step-down between intensive care and ward-based care.

The main finding is that, in our cohort, the need of resources increases in parallel with the ascending risk of physiological deterioration, with severity of organ damage and with clinical complexity (as revealed by the similar trends in the four tools). Similarly we highlighted a moderate positive correlation of RT score with NEWS.

In accordance with this, the HDU division accommodates the patients with the highest NEWS and the highest RT sum. Both of these tools accurately described the de-facto intensity of care stratification in our population.

The need of resources (RT score) correlates with LOS. Moreover RT low risk category is useful to identify patients that will need in-hospital resources for a further short time: we can roughly hypothesize that patients with RT≤3 will be discharged in less than 6 days.

Interestingly the other main determinant of LOS is the clinical complexity. Patients with a higher burden of co-morbidities stayed longer in the hospital globally and after assessment.

On the other side neither the resource use, nor physiological deterioration are correlated with mortality. Severity of organ damage seems to be the only determinant of the risk of death.

The majority 85% of the patients in the study had a high RT (8) and the distribution in the other RT categories was unequal, with nearly 10% of patients in the lower categories (RT=0 or RT=3) and only a few in the others. The RT score (when the highest level of critical intervention was



considered) was similarly high (mean 7) in all three divisions, that on the contrary differed in their patient's risk of deterioration, severity of organ damage and complexity.

This study described a clear picture of the inpatient population of our hospital by demographic data and by the score results. Gers' patients obviously are older, but also have the highest co-morbidity burden, with all patients in the highest category at CCI. On the other hand, HDUs' patients showed the highest prevalence of COPD, obesity (with its pulmonary complication) and acute pancreatitis; they showed the highest rate of patients with risk of deterioration and the highest rates of patients with altered oxygen saturation. This is in line with the mission of Emergency Medicine that treats younger patients with acute severe illness and with a lesser degree of chronic co-morbidity. NEWS is a tool built and used daily in the UK for clinical decisions about monitoring and increasing level of care; in Italy, it is not so routinely used but *de facto* the assignment of patients to the HDU follows similar standards.

The IM ward presents a miscellaneous of acute patients with NEWS and SOFA on intermediate values, mostly with chronic co-morbidities as shown by the prevalence of cancer and chronic liver disease.

The difference observed between the peculiar characteristics of NEWS, SOFA and CCI in the three wards in comparison with the substantial “plateau” of RT score could be interpreted, in our opinion, considering the purpose that inspired RT. It was created to classify patients that needed the minimum possible of in-hospital resources, but in our overcrowded hospitals, we are used to **keeping** only inpatients that need many resources and to discharge the others **earlier**: **this** could explain the ceiling effect on the observed RT values. Moreover **we highlighted that** RT score cannot differentiate resource use for severely ill patients from the use due to chronic conditions. For instance, the 8 “oxygen dependent” of RT does not distinguish between acute hypoxia and chronic hypoxia with use of oxygen bottles at home; this is accurate in disaster response because oxygen is one of the most exhaustible critical resources, but in the daily ordinary situation the same is not true.

**To overcome this RT limit** we considered the sum of all the interventions (RT-sum), that could be a proxy of the level of care. **We showed a moderate** correlation of RT-sum with NEWS, a weak correlation with SOFA. The acutely ill HDU patients had the highest RT-sum, the highest need of interventions, in comparison with patients from the other divisions. Interestingly, however, the second-highest RT sum was in Ger ward, where NEWS and SOFA showed the lowest values. This could be related to the high CCI observed in the geriatric patients.

We could hypothesize that the level of care described by RT sum is dependent on the illness severity on one side and on the co-morbidity level, accounting for the clinical complexity, on the other one.

Probably RT-sum and NEWS are the most concordant and most useful tools to guide inpatient disposition, particularly to decide transfer to higher level of care, and this is in line with the common use of NEWS. On the other hand, if we focus on the discharge process RT score can predict which patient will be discharged in the next days, but the evaluation of complexity should be also taken into account. SOFA on the contrary is the stronger mortality predictor in our study.

This study was useful to describe the characteristics of the inpatient population in our hospital classified according to clinical severity, complexity and level of care. The emerging picture is of a great majority of urgent admissions from the Emergency Department. The majority of patients were over 65 years old and showed a high level of comorbidities. This is in line with previous papers that described the recent changes in health-care use [4, 36-37].

The majority of our patients used a lot of resources (high RT), showed clinical complexity (high CCD), nearly 1/3 of them were potentially evolving at the NEWS and 1/3 to half of the patients in the different divisions were over the SOFA cut-off. This finding is in accordance with the reported use of in-hospital resources reserved to the more severe, acute or complex cases [36-37]. In this scenario, we should suggest that the RT score, the RT sum and NEWS score could be integrated into a decisional algorithm for optimal resource allocation and assignment of the correct level of care.

#### Limitations:

The main limitation of our study is the unequal distribution and low variance of RT score in our population with its ceiling-effect that could have impaired the correct evaluation. Anyway, the data analysis with subgroup categorization and the use of the continued variable RT sum tried to overcome this limitation.

The use of RT as the sum of interventions, although intuitive, in our knowledge was never described in previous studies; our study could probably pilot its use after further validation studies. Finally, our data could have been biased by the fact that severely impaired patients were sometimes not able to give informed consent and thus were not included in the study, leading to underestimation of data in the highest categories of RT, SOFA and NEWS.

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Figure 1 legend

Figure 1 shows correlations between RT, considered as the sum of all the interventions (RT sum) and NEWS score, SOFA score and CCI score respectively. r and p values are calculated according to Spearman correlation

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