SmartScale-A-Hospital

Developing a whole-hospital simulation framework for pandemic resource planning

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ABSTRACT

As we have seen during the SARS-COV-2 pandemic, it is vital to reserve enough intensive care capacities so that both regular and infected patients can be treated. Hospitals have increased their intensive care resources by re-purposing beds and deferring non-vital treatments, thus freeing up medical staff for work in infectious wards or as a backup. However, this re-allocation has been conducted in a best-effort manner, using rough estimates rather than more formal quantitative methods. In our work, we have tried to produce a whole-hospital simulation that allows assessing the effects of capacity re-allocation in regular and pandemic operational contexts. As a result, we are able to get a better insight into how many resources are needed and what can be allocated to other purposes.

CCS CONCEPTS

• Applied computing → Forecasting; Health care information systems;
• Computing methodologies → Agent / discrete models.

KEYWORDS

Pandemic, resource allocation, hospital, simulation

1 INTRODUCTION

During a pandemic, mortality correlates with the availability of free intensive care beds – both for acute conditions such as cardiovascular diseases as well as the pandemic disease itself [11]. During SARS-CoV-2, governments around the world have therefore concentrated their efforts on ensuring free capacities in ICUs by reducing transmission within the population. In clinics, these efforts have been complemented by postponement of non-vital treatments, leading to a decrease in regular patient volume. This in turn reduced the risk of infection for patients and staff, further leading to possibilities for establishing a safety buffer (people working from their home office, ready to stand in for infected colleagues) or reallocation for treatment of infected patients using additional bed capacities (e.g. from anesthetic recovery rooms).

Planning for these changes was often difficult given the rapid development of the pandemic [8]. Since no precedents existed, measures had to be taken based on future estimates of the pandemic curve and its influence on the expected amount of hospitalizations. Now that we have data for at least the first two waves of the pandemic, it is time to ask whether one can put at least the allocation of beds on a firmer quantitative basis.

Analysis shows [2] that the relationship between pandemic curve and hospitalization is non-linear (e.g. because of advancements in treatment). As a consequence it is not possible to analyze the data we have as a whole and arrive at aggregate conclusions, since that would silently ignore its diverse nature. In this work, the authors have tried to simulate and compare pandemic and regular operations day-wise, much in the fashion that commentators compared the current state of pandemic to certain days in the first and second wave. Our simulation framework (general description in section 2) contributes the following aspects:

- We take a close look at patient flow data readily available in clinics, which can be used to infer organizational structure and patient flows on a daily basis (section 3).
- We discuss the use of patient flows gathered during regular and pandemic operations in a resource allocation simulation which shifts bed capacities between regular and infectious beds (section 4), allowing to either maintain operations during both regular and pandemic cases, or to down-scale and adapt bed resources only to the pandemic case (thereby releasing staff resources).
- We perform a critical analysis of the former point and adapt the simulation so that patient flows can be generated, taking (1.) an appropriate baseline in which (2.) we decrease regular patient flow for non-critical activities and (3.) a pandemic
volume taken from observational data is introduced (section 5); the simulation thus becomes an emergency planning tool. The concepts presented herein may deviate significantly from the usual way of conducting hospital simulation: In regular regular operation, one can assume that patient volumes are relatively homogeneous. In pandemic cases, however, patient volumes are composed of infectious and non-infectious patients which have varying characteristics throughout the course of the pandemic. An in-depth discussion on this difference is given in section 6.

2 GENERAL DESCRIPTION AND BACKGROUND

Our framework uses Discrete Event Simulation (DES) [9] for modelling hospital departments as capacity-limited servers with queues (see figure 1a). Depending on department type (inpatient/outpatient ward), we may regard the capacity of a department as number of treatment rooms, beds, or processing capacity (in case of a lab).

Figure 1: (a) Department as server with a certain capacity, being utilized over time by service requests. Utilization above the capacity line yields a queue. (b) Schema as layered lattice of cells each labeled as (horizontal/vertical) circulation or as cell belonging to a certain department. Agents representing patients move within that schema, executing their service schedule and performing wayfinding between consecutive departments.

Likewise, queues which form as result of too many service requests can be interpreted as space requirement for waiting areas (with or without social distancing rules), also taking into account priority and type (walking, seated, in bed) of patients within the queue. In the temporal domain, we can further impose idle durations between service utilizations, thus modeling additional cleaning times and forcing inter-arrival gaps for avoiding airborne transmissions.

These departments are being utilized by agents which represent patients (figure 1b). Each of these agents has a schedule of departments to visit and time to spend there (i.e. service time). Schedule-based agent simulation has previously been conducted by a multitude of authors, e.g. by [4, 17] in the context of office building occupancy simulation, based on exported calendars of building occupants or by explicit surveying; in our model, we use data from a Hospital Information System (HIS) to achieve the same goal (similar to [20, 21]; also see next sections), even though the data quality does differ greatly from the aforementioned (discussion in section 6).

In terms of literature, this approach qualifies as a mixed DES/Agent-based system[6] with a process-based connotation; however, our agents just “travel on rails” from one department to the next department, not having a will of their own – they “just” perform pathfinding using a shortest path algorithm [either Dijkstra’s algorithm or A*, depending on configuration]; this is in harsh contrast to other authors (e.g. [14, 17]) who employ behavioristic rules along the way, e.g. introducing some additional time for chatter if agents meet, or having shared meetings where the service times depend on more than one individual, such as a team in the Operations Theater (OT) waiting for the anaestesiast.

With regards to space, the agents move in a schema which is represented as 2.5D square lattice (figure 1b: here we see multiple levels of a 2D square lattice, one for each floor). Each cell of the lattice is marked as “horizontal circulation” (default; yellow in figure 1b), “vertical circulation” (yellow with lift symbol) or “belonging to a certain department” (other colors in figure 1b), respectively. The 2.5D lattice is the spatial model of our approach, on which we additionally overlay the floor plan of the actual hospital (see figure 2).

2.1 Whole hospital simulation

Approaches for simulating a whole hospital are seldom and largely not based on DES or Agent-based Simulation (ABS). For example, Harper and Shahani [5] present a bed capacity planning tool based on continuous simulation of patient flows between care units on multiple hierarchical levels (“may represent a ward, a specialty bed-pool or the hospital as a whole”; ibid. p. 12). In the same direction goes [16], which uses System Dynamics (SD) for evaluating whole system operational performance.

Authors that do use DES for whole hospital simulations generally simplify the model using only certain representative departments (e.g. [10]) and perform a patient flow simulation in order to find bottlenecks that occur in significant parts of the system. Another approach which supports larger structures is the composition of servers representing departments into hierarchies [22].

The split of departmental capacities into resources serving regular and infected patients is novel to the best of our knowledge, at least on the DES hospital simulation level; however there are mixed DES/ABS approaches on the population level that clearly distinguish between these resources (Standard Bed/ICU Bed, see [3]), and there are recent DES simulations for the mitigation of capacity-dependent death in intensive care [19] which also have this notion.

3 PATIENT FLOW DATA IN PANDEMICS

HIS offer an interface with which it is possible to export patients’ movements in tabular form (e.g. SAP IS-H Movement Data [13]). Besides that one can intercept individual patient messages within the clinical environment (e.g. extracting HL7 PV1 Segments [7]). However these messages and table entries may also contain the identity of the patient, and must thus be properly anonymized before further use.

As next step further problematic pieces of data that may narrow down an anonymized row set must be removed (e.g. case number, sex at birth, age, address, city). Even though perfectly anonymized
in principle, it would still be possible to guess the identity of a person when the cohort size is too small (or put otherwise: if there was only one person undergoing treatment in a department, it is possible to guess this person’s identity). Small cohort sizes per department are the standard (not the exception; unless perhaps in Accident and Emergency [A&E] departments) and thus it is not feasible to eliminate all data points for keeping indirect privacy.

One ends up with a data-set that resembles the one shown in table 1:

- (PSEUDO) ID gives the anonymized patient ID which serves as a common bracket to later entries
- DATETIME gives the instant the encounter occurred; the table is sorted in ascending order by this column
- ORGUNIT gives a department name
- TYPE gives the patient type (infectious or regular)

Expressing DATETIME in table 1 relative to the first timestamp and aggregating by (PSEUDO) ID yields a data-set containing the sequence of departments that a patient has visited (this is also called patient flow, see table 2). Additionally computing the DATETIME delta between consecutive visits of a patient yields an estimate of the maximum service duration [see again table 2, e.g. IM2ST(00:20:00)]. Note that one cannot compute the service duration for cases in which there was only a single visit (cf. table 2: RADAM(?)). In that case, a default service time per department has to be taken, which might also be derived from all other (known) service times of that department (e.g. by averaging).

Additional metadata may include classical categorizations such as “walking, seated, in bed”, “inpatient or outpatient”, and so forth. As said previously, these may inform the architectural design as

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**Table 1: Example of clinical movements exported from HIS**

<table>
<thead>
<tr>
<th>(PSEUDO) ID</th>
<th>DATETIME</th>
<th>ORGUNIT</th>
<th>TYPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15.1.2020</td>
<td>IM2ST</td>
<td>infectious</td>
</tr>
<tr>
<td>2</td>
<td>15.1.2020</td>
<td>RADAM</td>
<td>regular</td>
</tr>
<tr>
<td>1</td>
<td>15.1.2020</td>
<td>RADAM</td>
<td>infectious</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

**Table 2: Clinical movements transformed to flows**

<table>
<thead>
<tr>
<th>(PSEUDO) ID</th>
<th>START</th>
<th>FLOW [ORGUNIT(DURATION)&gt;…]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>00:00:00</td>
<td>IM2ST(00:20:00)</td>
</tr>
<tr>
<td>2</td>
<td>00:01:00</td>
<td>RADAM(?)</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

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well as hospital management about the nature of each individual patient flow.

3.1 Organizational structure from flows
To obtain the structure of the hospital, we extract all distinct departments from all the patient flows, which is sufficient for simulation since only patients are considered. For each department we select the total capacity (i.e. beds in case of inpatient wards or service stations in case of outpatient wards; see left part of figure 2). We furthermore specify how much of that capacity is reserved for infectious patients.

3.2 Linking departments to the floor plan
After having inferred the organizational structure of the hospital we import the floor plans (middle part of figure 2). Each of these plans each being rasterized into a square lattice of equally-sized cells with a given scale. Each department can then be assigned one or more of these cells, so that we can represent them spatially. One can additionally attribute cells as being part of the horizontal or vertical circulation (also recall figure 1b) so that agents move realistically through the virtual hospital. A cell can thus be both a department cell and part of the circulation. As per default, all cells belong to the horizontal circulation. Vertical circulation uses a different movement speed currently, and might be supplemented with a lift simulation (using capacity-limited servers = lifts) in the future.

3.3 Flows at different instances in time
Our simulation looks at multiple days which we export separately. As baseline, we take a typical day in non-pandemic times – e.g. Wednesday 15th January 2020 (see top part of figure 3). This flow data-set (or simply flow) is then compared to other days during the pandemic, as explained in due course.

4 SIMULATING REGULAR AND PANDEMIC PATIENT FLOWS
In our simulation, we use a baseline flow and one or more pandemic flows as input. The computation instantiates each patient within the flow at the appropriate simulation time (see column “start” in table 2) and tries to allocate the first department for that patient (e.g. IM2ST for a duration of 20 minutes). Depending on patient type (infectious/regular), the simulation uses either regular or reserved capacity in that step (see again 3.2). If the department can be allocated, it will be used for the specified service duration (see column FLOW [ORGUNIT(DURATION)>... in table 2). In all other cases the simulated patient is put into a queue (i.e. waiting occurs). The simulation process continues until all patients have executed their schedule.

The simulation results can be reviewed visually by looking at the utilization statistics (right part of figure 2):
- If the black utilization line of each patient flow stays below the red capacity line, then no waiting occurs both in the regular as well as pandemic case; this can be used to model inpatient wards which have to maintain operations during both regular and pandemic cases; the basic question in that context is: Are there enough spare beds so that some could be turned into infectious ones (given proper isolation of the newly-created area, which is beyond the scope of this paper).
- For outpatient wards with waiting areas, we can guarantee enough resources for regular and pandemic operation even if an over-utilization up to capacity + number of waiting places is given (visually, the black utilization line would exceed the red capacity line in that case). Again, the physical implementation of the and access to the two formed waiting and examination areas is beyond the scope of this paper.
- If the goal is to scale down non-vital resources for the pandemic case (thereby releasing staff for (a) reassignment to other areas such as infectious wards or (b) having a backup on standby), then reserving enough bed capacities such that utilization stays below the threshold for the pandemic patient flow is sufficient. Caveat: Some areas, such as A&E, will have to be kept open and might require more staff and space resources because of the needed separation between infectious and non-infectious patients. However, since the according patient volumes are already present in the respective pandemic flow, the above statement still holds.

5 GENERATING PATIENT FLOWS: SIMULATION AS AN EMERGENCY PLANNING TOOL
Up until now, simulation has been conducted with reference to historic data during regular operation (figure 4a) and pandemic operation (figure 4b). The key was to exploit the similarity between the expected patient volume, in the sense that one expects to see the same patient volumes as in a first wave also during a further wave, in cases where the number of infected are approximately equal (figure 4c). However, this is not always the case because of seasonal effects such as the flu season influencing the patient volume (compare with figure 4c: the beginning of October might already be affected by the start of the flu wave), or vacation and celebration patterns (e.g. summer vacations, Christmas). One should also note that comparisons between different patient flows are better defined by means of reserved bed utilization rather than pandemic incidence (which, in the concrete case presented in figure 4c would shift the comparative period to end-October [12] instead of mid-September to mid-October).

What is needed is a method that does not take the historic data directly, but uses it to fit two distributions for each department, (1.) arrival times and (2.) service durations. Using the expected patient volume of each department, we can then generate a future patient volume against we can test the regular and reserved capacities.

In our approach we use Kernel Density Estimation (KDE) with a gaussian kernel and Scott’s Rule [15] for estimating bandwidth. Since the resulting distribution might range into the negative number range, we have to truncate it at 0 and renormalize the positive part. An illustrative example is given in figure 3: Here we see that the distributions for both arrivals and durations are generally multi-peaked and left-leaning. There are, however, large variations depending on the type of department, which impedes fitting single distribution (e.g. Weibull, Poisson); KDEs, on the other hand,
Figure 3: Patient arrivals and service durations for clinic Zams surgical outpatient department (CHABT:CHAMB), as histogram (gray bars) and gaussian kernel density estimation (blue lines). (1st row) Regular operation on 15th January 2020. (2nd row) Peak of the 1st wave of the pandemic. (3rd row) Begin of the 2nd wave of the pandemic. (4th row) Same period as 2nd wave, but one year earlier.

Figure 4: Patient flows during (a) regular and (b) pandemic operation. The latter seems to hint at similar patient volumes for (c) later instances with approximately the same amount of infected persons, however this is not the case because of e.g. seasonal effects. Image derived from [18], used under terms of CC0 1.0.
adapt to the underlying data without needing to choose a classical distribution for which a parameterization is sought.

5.1 Choosing a baseline

Seasonal effects such as the annual flu wave as well as injuries and diseases in direct connection to vacation times (e.g. sports injuries) need to be taken into account when choosing a baseline for a simulation; this demands that chooses a target period (e.g. season, work period/vacation period, or month). For the established target period, we take the working week (Monday - Friday) as a reference [Saturdays and Sundays are outside of our scope since operations during week-ends need to be considered as a special case, with almost all outpatient departments being closed and most of the staff absent]. Using data of that period we can arrive at “regular” patient arrival times and service durations, in the same fashion as the previous (real) baseline flow depicted in figure 3a. The difference is that this baseline is now situated in the target period for which planning is conducted (figure 3c), and might now include seasonal effects of that period. In our example in figure 3, the baseline period is given in the fourth row [09-14 - 10-30 (2019)]. Comparing that with the data during the pandemic – i.e. third row [09-14 - 10-30 (2020)] – shows that there is almost no difference between regular and pandemic operation. The same would not hold e.g. for the Intensive Care Unit (ICU).

5.2 Scaling down non-critical services

Because we are simulating a whole hospital rather than a single department, it would be unviable to look through every single diagnosis associated with a visit in order to find out whether it could be postponed. However, such an information is needed if we want to scale down all non-critical services. We argue that this scaling down is best done with reference to expert knowledge, yielding a department-wise factor which is

- close to 0% in cases where operation cannot be scaled down because demand is constant (predominantly outpatient departments, e.g. A&E) or must always be provisioned, regardless of volume (e.g. because of safety considerations)
- 0-100% in all other cases, dependent on a manual analysis of all medical services provided according to department type and season Different department types can typically taken from national regulations and structure plans which offer a standardized catalog (e.g. [2] in the case of the authors). The result of this a-priory analysis is recorded and can be applied to other hospitals in subsequent cases.

All in all, we derive a reduced patient flow for pandemic cases using these pre-calibrated rates, possibly also overriding these values manually in cases of non-standard departments or reasons that follow a logic other than possible volume reduction (e.g. safety considerations, regulations).

5.3 Inserting a pandemic patient volume

The arrival and duration distributions that have been fitted using data from the 1st wave (see 2nd row of figure 3) needs to be scaled to the expected number of patients per department in order to arrive at a pandemic patient volume. Epidemiological projection (e.g. [3]) can be used to arrive at incidence, however, one cannot map this directly onto the expected number of patients in each department.

What is given are the numbers of patients during regular operations [as outcome of analyzing the target period during the last year(s)]. Some departments are not affected by the pandemic (comparison baseline to 1st wave data) and thus no pandemic volume is generated for them. In cases where we have encountered a pandemic patient volume during the first wave, we have to

- find the ratio between the number of infected patients and the average incidence during the sampling period of the 1st wave, for each department,
- multiply this ratio by the projected incidence to arrive at the number of expected patients

As always, in some cases there is need to overrides these calculated numbers, if for example face validation contests these results. Heterogeneous assessments and/or (min,max-)deviations in epidemiological projections necessarily lead to different pandemic flows which can be simulated as part of different scenarios.

5.4 Running the the simulation in multiple scenarios

The simulation is run against the baseline and the scenarios mentioned under section 5.3, giving a projected (min/max) resource utilization for each department; the final goal lies in adjusting the resource capacities both for regular and reserved resources such that the demand of each scenario can be met sufficiently. Generally this will mean “scaling down” capacities such that the minimum number of resources can serve each respective patient flow, thereby freeing resources for work in the home office, as a buffer in case staff gets infected, or simply as a safety precaution so that only a minimal required amount of staff is present.

6 DISCUSSION

6.1 Converting resources to staff and equipment

‘Resources’ are not simply people or beds. When we talk about resources and capacities, we eventually mean staff and/or equipment such as beds. However, the conversion between the two is dependent on context – the staff allocation plan, work regulations, equipment being used, and so forth: Consider, for example, the case of an outpatient department where ‘resources’ are mainly beds, however, attached to these come staffing needs (different for regular and reserved i.e. infectious beds; also subject to different regulations concerning e.g. allowed working hours with and without protective equipment worn). These matters are complex at the hospital level, however they are easily resolved and on the department level where procedures are well-established and resources can often be translated directly into staffing needs, equipment and – most importantly – spatial requirements such as separating walls, distance markers and seats marked as unusable. Such spatial requirements could also be included into our simulation in the future.

6.2 Use of observational data

We base our approach on observational data gathered during e.g. the first wave of a pandemic, which we scale according to some target parameter (e.g. incidence). Thus, the data is already “generated”
in a sense. Implicitly, we assume that the same mix of patients observed in the initial stage will also appear in later stages, which is sound if the characteristics of the virus causing the pandemic does not change due to e.g. mutations, or the spread is not changed drastically e.g. by vaccination. Still, one could model such effects by editing the scaled data, however this would be unviable since that would have to be done for every target parameter (i.e. scenario) and every department. Generating patient flows out of thin air would amount to pure guessing, we argue that at least some historic data (e.g. SARS, MERS, COVID-19) needs to act as a seed so that we have at least some degree of plausibility. This data is easily exported from hospital information systems, as outlined previously.

6.3 Choice of data range

Initial observational data from a first wave is composed of a ramp-up phase, a plateau (or peak) and a decline phase (figure 4b). Apart from these phases, we have data during the week and at weekends, with very different characteristics (also because the parameters such as incidence might not be reported accurately for the latter). Additionally we have vacation vs. regular times, additional pandemics such as the annual influenza skewing the data set. Extracting initial observation data thus needs close attention to the temporal and epidemiological context. While developing the simulation, we chose to extract data from the peak [because that was our target period, relatively stable and luckily not during the vacations for COVID]; for obvious reasons we furthermore excluded week-end data. When targeting other periods than the plateau, however, it might also be a good choice to extract data from the ramp-up or decline phase, and there is certainly a lot of insight to be gained from comparing the quality of these two periods with the peak phase (future work).

6.4 Capacities assumed constant

We assume a fixed capacity per department while in reality such capacity can change both for the regular and the pandemic case: Consider, for example, a clinic in a skiing region where the amount of beds increases during the vacations; or the COVID-19 pandemic, during which the amount of reserved [intensive care] beds changed from day to day. This is clearly a simplification of our model that is likely going to change in the near future.

6.5 Pre-utilization effects

Wards and outpatient areas might already be populated with patients from the period before, thus leading to an effective capacity than is less than the assumed one. We have so far not included these effects into the simulation, but will likewise look to include this very important factor in the future. How to get the predicted utilization will be an important aspect in that context.

6.6 Transferability of a-priori analysis

As stated, we perform an a-priory analysis of departments during regular operations to obtain the percentage of activities that could be scaled down in the pandemic case. The question now is if we can transfer the results of this analysis to another hospital. Currently we have no clear answer for this, because our data comes from a single hospital. It is clear that the patient volume is dependent on the hospital type and catchment area, and also depends on seasonal effects; rather than saying no immediately, it would be beneficial to look at other departments of the same type (cf. [1]) in a different region of the same country, and to compare how these percentages are similar. To move beyond national boundaries would be a next step further down the road.

6.7 Weighting scenarios

Different parameters being used to obtain the scaled patient volumes lead to different (min/max) utilizations. Weighting these scenarios’ utilizations might be used to obtain an “average prediction”, however, how that should be done so that this average is meaningful is still unclear to the authors – results could be arbitrary if not done right. Therefore, we have opted to shift this subject also to future work, since it requires careful thought on each parameter used for forecasting.

6.8 Data quality

We use exported movement data from HIS to obtain our patient flows. The data in itself might already be erroneous if sampling is not done correctly (refer to figure 5): Every patient schedule can be described as succession of activities, where each activity takes place in a capacity-constrained service area with a queue in front. The durations spent for the activity can thus be decomposed into (duration for queueing, service duration and optionally duration for walking to the next service point).

Figure 5: Schedule as sequence of duration triplets (queue, service, walk)

The movement data (cf. table 1) contains a timestamp located in between entering and leaving the service point (“A” and “B” in figure 5). When taking the delta between timestamps of successive activities, this might overexaggerate service times if queueing takes place (figure 6). Also the last service duration cannot be reconstructed.

Figure 6: Reality vs. observation of movement data
A better way would be to give two timestamps (at A and exactly B) instead of one. If that is not possible, the service timestamp should at least be sampled exactly A or B and not in between; since one knows the duration for moving to the next service point (shortest path within the schema), one can deduct this duration (shown black in the upper part of figure 6). One can furthermore estimate queueing durations (at least for outpatient departments) as delta between patient registration and service timestamp. If we deduct that also, we get a corrected service duration. However, these ideas are theoretical for now and remain untested in practice, we have it on our agenda for future work.

7 CONCLUSION

We have presented a whole-hospital simulation framework for resource allocation in pandemic scenarios, simulating patient flows that reserve departments (i.e. servers of a discrete event simulation) which have a certain capacity in terms of regular and infectious patients. In that context we have contributed a workflow for resource planning using observational data of a first wave. Our approach allows better insight into how many resources are needed and which resource can be re-allocated when dealing with a pandemic. The tool is targeted at hospital administration and healthcare planners, and allows for a quick prediction of a whole hospital in a matter of hours as opposed to a detailed look at departments where modeling and simulation may take months. In that spirit we rely on anonymized patient movement data that is readily available within every hospital information system, so that data preparation can be kept at a minimal level.

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