

# Knowledge Management in Healthcare: Information Requirements When Creating a Decision Support Tool in Radiology

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**Keywords:** Business Process Modelling, Health Information Systems, Discrete Event Simulation, Workflow, Patient Complexity, Resource Utilisation, Computed Tomography, Radiology.

**Abstract:** Introduction: This empirical work examines the information requirements when undertaking a process modelling project in a Healthcare setting such as a CT (Computed Tomography) department. Using qualitative and quantitative methods we map the process, incorporating patient, staff and process related components so as to quantify resource utilisation and the service experienced by the patient. Method: In this study, semi structured interviews are used to identify patient complexity factors/characteristics. Process mapping and involvement of stakeholders are discussed as is the identification and analysis of data. A discrete event simulation (DES) model of the process is designed and performance metrics identified. Results: Yearly demand for Radiology services are increasing significantly. Factors determining patient complexity and variation include patient type, infectiousness, mobility, exam type and patient care needs. A strong correlation between age and infectiousness was observed. Conclusion: DES modelling, though data intensive, provides decision makers with insights into resource utilisation, process capacity, delays and disruptions and in doing so supports operations, management and the adoption of good practices in Healthcare.

## 1 INTRODUCTION

Radiology departments have adopted many strategies to continually improve aspects of radiology workflow. Many departments are reengineering their workflow to eliminate and automate steps in the process and to make more intelligent use of available resources and software. In healthcare the shift towards evidence-based management has been supported by the adoption and adaptation of management methodologies. Included amongst these philosophies are; Lean Thinking, Queuing Theory, the Theory of Constraints, Six Sigma and System Dynamics. (Gahan, 2010) This empirical research, using discrete event simulation (DES) as a decision support tool, identifies how patient variability and the increasing demand for CT affects resource utilisation, staff workload and the service provided to patients.

The challenges facing radiology service provision are many. The number of over 65 year olds will double between 2011 and 2031 (Central Statistics Office., 2015). The increasing prevalence of diabetes and obesity among young people

suggests that future elderly cohorts might even be less healthy (Lakdawalla et al, 2004; Sturm et al., 2007). Resources are limited and the demand for Radiology services is increasing year on year.

Simulation allows offline experimentation and process redesign as well as the pre-emption of unintended consequences while minimising disruptions of the current system. Examples of the application of modelling and simulation involving radiology departments are many (Booker et al., 2016; Jin et al., 2011; Lu, Li & Gisler, 2011; Rachuba et al., 2018; Reinus et al., 2000; Shukla, Keast & Ceglarek, 2014). One radiology model example uses patient characteristics to determine length of procedure time, these are where the patient is referred from, appointment time, gender, mobility, and body area to be studied. (Huang & Marcak, 2013).

Simulation modelling can capture undesirable behaviours in response to work pressure, such as staff turnover, erosion of service quality and fatigue, all examples of unbalanced responses to increases in workload (Oliva, 2002).

Radiology has been referred to as an “anti-care”

area due to the short time periods spent with patients. Radiographers see care as a wider concept that encompasses administrative and technical elements as well as a relational element (Brask & Birkelund, 2014). While much has been found on quantifying Radiologist workload (Cowan, Macdonald & Floyd, 2013; Pitman et al., 2009; RCSI, 2011) little literature on Radiographer workload has been discovered. Further research into the pressures specific to the time-pressured, task-focussed and highly technical environment of radiography and the impact on compassionate patient care has been recommended (Bleiker et al., 2018).

When high work intensity is sustained over long periods, time per order and service standards will gradually decrease leading to high burnout rates. (Oliva & Sterman, 2001). Using qualitative and quantitative methods we determined the patient related factors and characteristics that contribute to delays and modelled the patient journey through CT. This virtual or digital “twin” of a CT department allows experimentation with staffing, schedules, additional scanners and demand levels. Metrics monitor the effect of these changes on the staff workload and patient experience as well as resource utilisation and waiting lists.

This research seeks to quantify the effect of mixing scheduled and unscheduled patient groups, on resource utilisation, using DES. Radiology model examples were not identified in the literature which simultaneously capture patient complexity and service received as well as resource utilisation and

radiographer workload. This holistic model has the potential to support daily operations and longer term policy making, which includes both the patient and the staff experience in the department.

## 2 METHODOLOGY

Ethical approval to conduct the study and access radiology data was obtained from the hospital Board of Management. A mixed method approach was taken with ongoing validation and verification with stakeholders. The department modelled provides 24/7 acute surgery, acute medicine and critical care along with emergency department and maternity services. Following exploratory interviews with decision makers the following methodology was used:

1. Workflow mapping of CT process
2. Identification of required patient data
3. Analysis of data
4. DES model building and validation
5. Future simulations design.

Patient arrival, preparation, scanning and observation were mapped. Expert evaluations were made following mapping and model completion and revisions made where necessary. Figure 1 is a section of the model relating to patient scanning and staff utilisation. In this section resources, such as the staff required for manual handling, are seized and released for the task durations.

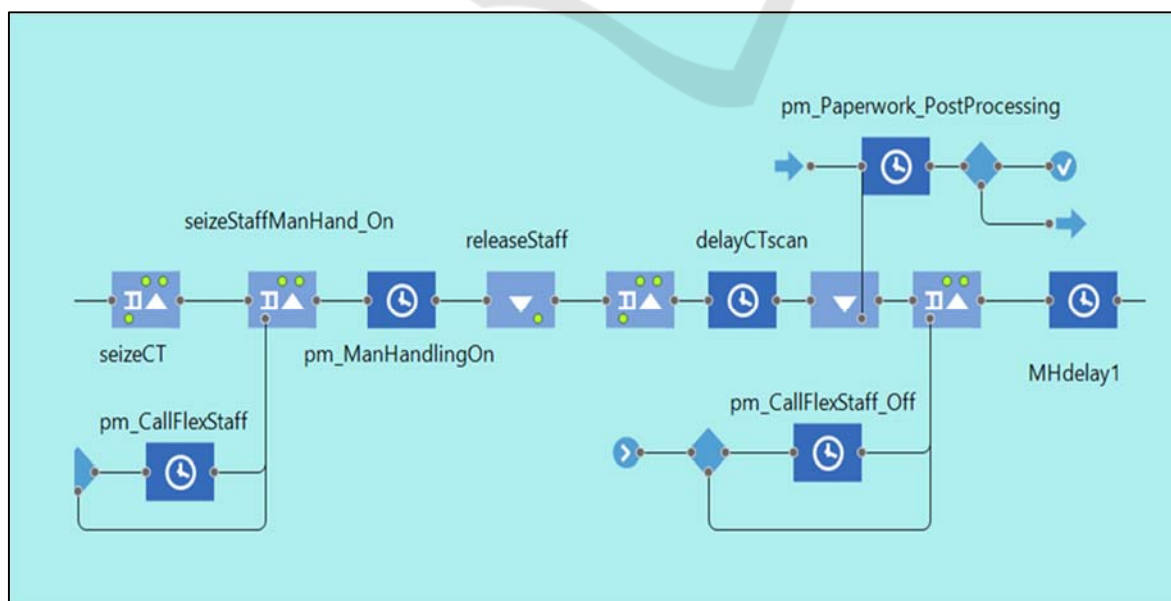


Figure 1: Model section related to patient scanning.

Data pertaining to over 10,000 CT examinations over a period of 2 years were analysed. Of interest were examination types, and time stamps for examinations being ordered, scheduled, arrived, ended and reported. Patients were categorised as either scheduled or unscheduled. Scheduled patients included outpatients and general practitioner patients and unscheduled patients included emergency department, medical assessment unit and Inpatients. Unscheduled patients automatically have a higher priority and are generally scanned on the same day as being ordered. Data was analysed to determine Poisson arrival rates for Inpatient and Outpatient orders. Outpatient waiting lists for CT scans and data pertaining to patient time spent in the department were analysed. Data was analysed in Microsoft Excel and R Studio (R Core Team, 2013).

Interviews with stakeholders including radiologists and radiographers were carried out to determine if the process maps were accurate and to discuss what factors impact patient throughput and staff perception of workload. Staff were asked the following questions suggested by Sterman (2000):

- Can you understand this model and its concept?
- Are the theories underlying the model correct?
- What’s missing from the model that should be included?

Feedback from the interviews was graphically collated in Figure 2. The patient related factors were identified and data obtained for same. Results from the semi structured interviews grouped the factors affecting radiology workload into the following categories.

1. Referring doctor requesting patterns and expectations,
2. Staff synergy and skill mix,
3. Environmental factors, noise, disruptions, distance
4. Poor use of Radiology information systems such as impacting on communications with wards and porters,
5. Patient characteristic factors.

Table 1 lists patient characteristic factors, their data type and the data source used. These factors were incorporated into the model. The software Any logic was used to create a DES model of the process (Anylogic Personal Learning Edition 8.4.0, 2019). The model includes logic, statistics and simulation pages. The statistics page consists of a dashboard including resource utilisation, activity breakdowns and performance metrics. The simulation page, provided the user with the facility to change the following:

- The number of radiographers and HCAs
- The number of scanners
- The arrival rate of patients (demand)
- Patient mix scenario
- Alternative scheduling options

The model was designed to export data to an excel spreadsheet on execution of the model. Patients were stochastically generated and CT start and end times captured. This model was developed for a specific purpose and its validity determined with respect to that purpose. (Sargent, 2013)

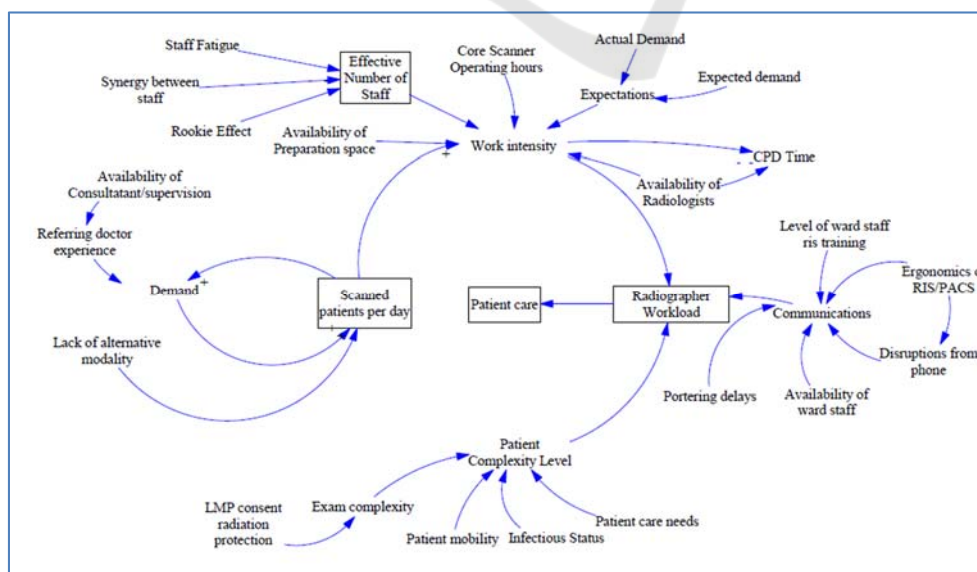


Figure 2: Graphical collaboration of results of stakeholder interviews.

A combination of techniques was used to validate and verify the model’s accuracy. Historical data was compared to the model data for validation. Comparison was made between mean length of time in system and mean errors. Face to face validation was used for model input parameters and assumptions. Animation was used to verify patient and staff flow through the department.

Based on the overall results of the validation and the endorsement by staff, it was affirmed that the simulation model adequately represented the process.

Table 1: Patient complexity factors and data sources.

Patient Factors	Data Type	Data source
Patient type	Scheduled or Unscheduled	Radiology Information System
Exam complexity	Defined by whether contrast intravenous contrast (IV), oral contrast, no contrast, IV and oral or procedure involving radiologist	Radiology Information System
Infectiousness status	Absence or presence of infection alert on system	Patient Administration System
Patient care needs	Administrative patient care captured by phone calls made to schedule Inpatients. Face to face patient care times observed.	Phone records observation
Patient mobility	Walking, Wheelchair or trolley/bed.	Online survey

### 3 RESULT

An analysis of yearly demand showed significant growth ( $p=1.05e-12$  which equates to 430 examinations per year) for unscheduled exams with no significant change in the number of scheduled examinations completed  $p=0.907$ . 73% of the work was found to be generated by unscheduled patients and the remaining 27% by scheduled patients.

Exam complexity refers to the type of exam, exam duration and resources required. A breakdown of all CT exams showed non-contrast (45%), IV contrast (20%), Oral and IV contrast (25%), Oral only (3%) and interventional (7%). IV and Oral refer to the types of contrast used in the scan to provide additional information to the diagnostic test. Each type of contrast has different preparation steps and requiring different resources and durations. When

further broken down into scheduled and unscheduled 64% of unscheduled exams are non-contrast compared to 33% of scheduled, Figure 3.

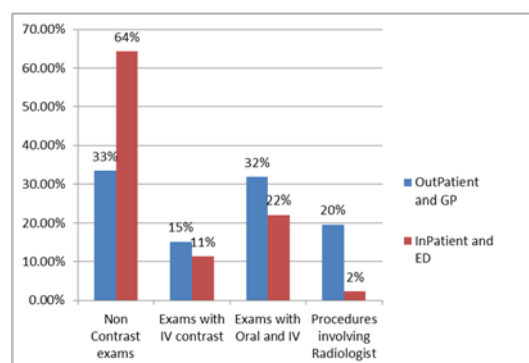


Figure 3: Inpatient/Outpatient breakdown by exam type.

Data on patient infectiousness was obtained from the PAS (patient administration system). Where patients identified as infectious an “alert” with the name of the infection appeared in their records. 8.8% of inpatients were documented as infectious ( $p$ -value: 0.965) thus requiring more staff time with scheduling constraints. Using logistic regression we conclude that infection rate increases with age (Figure 4), base infection rate of 1.5% and a ceiling of 36.6% with  $p<2e-16$ . Polynomial regression was used to determine the relationship between patient length of stay and likelihood of infection. As length of stay increases, the likelihood of infection is seen to increase,  $p$ -value:  $1.268e-07$ , Adjusted R-squared: 0.9683.

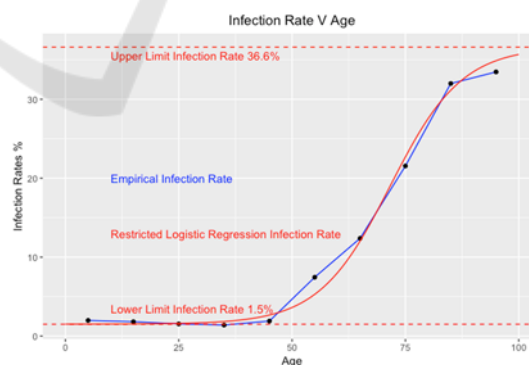


Figure 4: Age and infectiousness relationship using logistical regression.

A survey carried out as part of this work, reported that 26% of inpatients were estimated to have mobility issues, thus requiring a wheelchair or trolley/bed. This data was used to populate the DES model and incorporate time delays for patients with mobility issues. Additional staff are required to

assist with manual handling (transfer of patient onto the CT bed). These additional staff are called flexible staff and the time taken to call these staff and wait for their arrival as well as the time taken to carry out manual handling tasks are included in the model. From observation it was determined that a minimum of 4 staff are required for the manual handling transfer of a trolley patient, 2 for a wheelchair bound patient and 1 staff member is required to assist where the patient can walk.

Figure 5 graphs the phone traffic data to and from CT. 33% of calls were made to the CT control area and 67% of calls were made from the CT control area. On average CT staff make 2 calls to arrange preparation and transportation for patients and 1 call per patient from ward staff and referrers. Observational data was obtained for the more traditional face to face patient care that patients receive while in the CT department. Again inpatients were seen to require more time and had greater patient care needs.

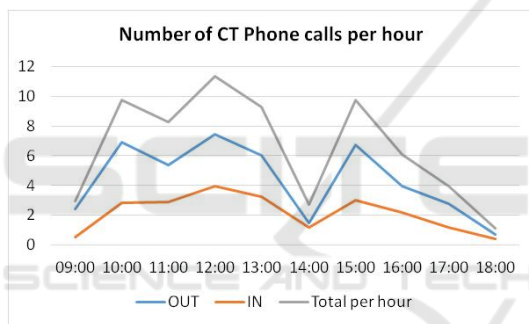


Figure 5: Phone activity related to inpatient scheduling. These general findings demonstrate the ability of the model to capture the following: Scanner utilisation levels.

- Staff utilisation levels
- Detailed task breakdown
- Number of flexible staff required
- Number of tasks completed per hour
- Average delays caused by patient type
- Average experienced by patient type

In the example provided (Figure 6), scanner utilisation was 62.5% between 9am to 5pm. 27 patients were scanned. Activities taking place in the room include patient scanning, room cleaning and patient preparation.

Similar charts show radiographer utilisation of 54.1% and health care assistant utilisation levels of 37%. Figure 7 provides a breakdown of staff utilisation by task type for each radiographers and a health care assistant on the same day. The pie charts were designed to include all administrative, clinical

and non-clinical tasks associated with scanning. Radiographer's staff spent 1 hour 29 minutes scheduling and answering calls.

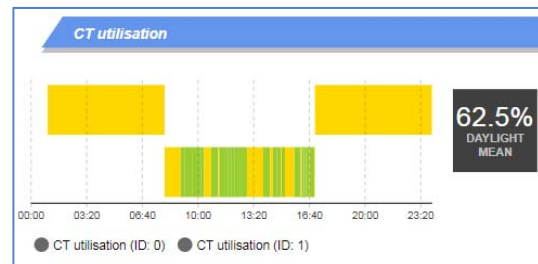


Figure 6: Scanner utilisation captured on DES model.

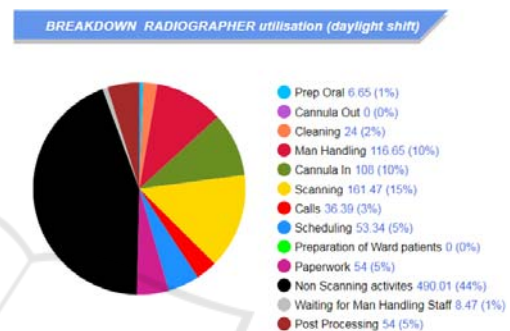


Figure 7: Staff utilisation by task.

The model captured the number of staff (36) that were required to assist with manual handling and the combined personnel time taken to do so (126 minutes). The average work perturbation (delays, disruptions, complications) for scheduled and unscheduled patients shows that inpatients caused on average 8 minutes more delays per exam (Figure 8). This is due to their manual handling needs, phone calls associated with their scheduling, patient care needs and transportation delays. The model allows the delays for each patient to be examined. In this way delays can be attributed to the patient's mobility or other characteristics and the process modified and staffed accordingly.

## 4 DISCUSSION

Outpatients are scheduled by administrative staff in advance of arrival. Using phone records we demonstrate the extra radiographer resources and patient care required to schedule an inpatient and Emergency Room CT examination. The increased administrative duties associated with unscheduled patients means that patient type is an important factor affecting radiology workload.

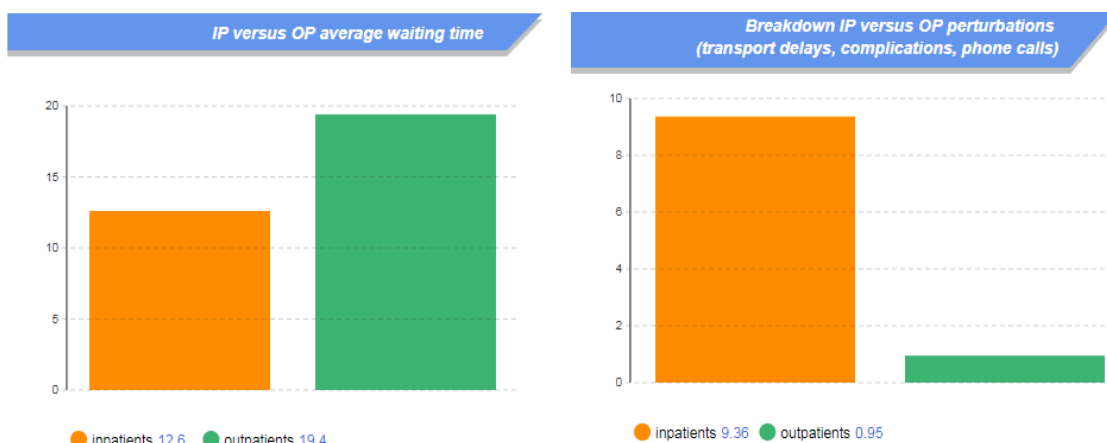


Figure 8: Average waiting times and average causes of delays by patient type.

There were 3 phone calls identified per inpatient exam completed. The information system, if used as intended, could potentially reduce this to 1 phone call or less per exam. An analysis of phone records indicates a suboptimal use of the information system. Some ward staff and referring doctors reported that they do not use the system to track patient requests and routinely place calls to verify a request has been received and that a time has been allocated. Peak arrival times for phone calls coincide with peak scanning time (Figure 5) so interruptions while scanning are common and represent a potential safety hazard as these occur at critical times such as when injections are being carried out. (Kansagra, Liu & Yu, 2016)

Infectiousness applies only to inpatient and emergency patients in this study as the infection status of outpatients is generally unknown, though universal precautions are taken for all patients. When a patient is determined to be infectious extra time is required to use personal protective equipment (PPE), isolate patients from healthy patients, and to allow for cleaning and drying time. A regression analysis shows a relationship between age and length of stay on the likelihood of infection. Exams, on which patient discharge depends, should therefore be expedited.

Patient immobility is seen to contribute to staff workload and results in delays. A patient transfer from trolley to scanner requires up to 6 staff. It takes time to transfer patients and extra delays occur where staff members are not immediately available to assist. Reliance on flexible staff to assist with manual handling incurs time delays in sourcing them and the DES model allowed this to be quantified. The extensive data analysis of the service and patient characteristics created a new appreciation for

tasks previously underestimated, in particular the time taken for the scheduling of inpatient exams and time spent waiting for manual handling assistance from flexible staff. This model creates metrics not previously available to managers such as the time spent scheduling and answering calls (1hr 29 mins).

The model outputs provide decisions makers with detailed data on how staff are utilised throughout the day and how work intensity varies throughout the day. Radiographer's utilisation was 54.1% and scanner utilisation was 62.5%, on this day where 27 patients were scanned. Each radiographer was scanning on average 15% of the time. Where a decision is required as to whether a new CT scanner should be purchased, this information can be used to support such a decision or to reengineer the current workflow. Separation of tasks as demonstrated in figure 7 can allow managers to decide how a radiographer's time is spent. Tasks can be identified as value adding or non-value adding and a lean approach taken (Liker, 2003). Lean manufacturing principles could be used to improve the flow of patients through CT, resulting in a reduction in time delays (Ng et al., 2010).

A metric was created for delays and disruptions which Reinus et al described as "schedule busters" resulting in workflow perturbations. Inpatients are seen to have higher work perturbation times than outpatients (8 minutes versus 1 minute) (2000). Currently a maximum of ten outpatients are scanned per day. The high variation in inpatient demand and associated work perturbations is cited as a reason for limiting how many are booked. Where outpatient lists are growing efforts can be made to block book outpatients thus reducing variability.

The model allows simulation of "what-if" scenarios such as:

- How block scheduling of similar outpatient examinations can increase standardisation of work and improve throughput.
- How pooling of resources between multiple scanners can improve staff utilisation and counteract work perturbations

Future work on optimisation of radiographer to health care assistant ratios and exam type scheduling using constraints such as acceptable patient time delays will be carried out.

## 5 CONCLUSION

Using qualitative and quantitative methods we determined the patient characteristics that contribute to process delays and efficiency while quantifying the growth in demand for Radiology services. The use of information garnered from the DES model described here, allowed a more informed breakdown of process capacity, which included patient mix and resulting inherent stochastic delays. As a decision support tool, it allows manipulation of parameters such as the number of staff, the patient mix and the number of scanners. Decision makers can use this model to experiment with “what if scenarios” and make evidence based decision in the best interest of the department.

Patient parameters such as mobility and infection and patient care are common amongst patients so the findings can be applied to other allied health services and in other healthcare simulation projects. Future work will use discrete event simulation to model the radiology service and simulate alternative service delivery models.

Inpatient demand is increasing while the outpatient service is stagnant. The demand for inpatients examinations is affecting the ability of departments to meet the demand for the outpatient and general practitioner services.

In the short term radiographers and other health care professionals have the capacity to absorb extra work without increase staffing levels, but modelling can allow us to assess workflow and workload, and staff accordingly so as to avoid unintended consequences, such as burnout, fatigue, staff attrition and poor patient care. The key challenges facing healthcare providers in future years may be more organisational and logistical than medical and scientific (Brailsford & Vissers, 2011). The model is intended to inform how patient complexity, interruptions, complications and the staff mix (radiographers and assistants) affect the capacity of a

CT process, so as to provide a detailed overview and understanding of the process.

DES provides a graphic tool for managers and models the patient the staff, the process and the information systems. DES requires high stakeholder involvement at each step of the way from conceptual model building to validation and simulation design. Simulation has been described as the main way we can discover for ourselves how complex systems work, what the impact of different policies might be, and thus integrate science into decision making (Sterman, 2011).

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## REFERENCES

- Anylogic Personal Learning Edition 8.4.0. 2019. Anylogic. Oakbrook Terrace Tower: AnyLogic North America. Retrieved from <https://www.anylogic.com/>
- Bleiker, J., Knapp, K. M., Morgan-Trimmer, S., & Hopkins, S. J. 2018. “It’s what’s behind the mask”: Psychological diversity in compassionate patient care. *Radiography*, 24, S28–S32. <https://doi.org/10.1016/J.RADI.2018.06.004>
- Booker, M. T., O’Connell, R. J., Desai, B., & Duddalwar, V. A. 2016. Quality Improvement with Discrete Event Simulation: A Primer for Radiologists. *Journal of the American College of Radiology*, 13(4), 417–423. <https://doi.org/10.1016/j.jacr.2015.11.028>
- Brailsford, S., & Vissers, J. 2011. OR in healthcare: A European perspective. *European Journal of Operational Research*, 212(2), 223–234. <https://doi.org/10.1016/j.ejor.2010.10.026>
- Brask, K. B., & Birkelund, R. 2014. “patient care in radiology” - The staff’s perspective. *Journal of Radiology Nursing*, 33(1), 23–29. <https://doi.org/10.1016/j.jradnu.2013.12.001>
- Central Statistics Office. 2015. Regional Population Projections 2016 - 2031 - CSO - Central Statistics Office. Retrieved from <http://www.cso.ie/en/releasesandpublications/er/rpp/regionalpopulationprojections2016-2031/>
- Cowan, I. A., Macdonald, S. L. S., & Floyd, R. A. 2013. Measuring and managing radiologist workload: measuring radiologist reporting times using data from

- a Radiology Information System. *Journal of Medical Imaging and Radiation Oncology*, 57(5), 558. <https://doi.org/10.1111/1754-9485.12092>
- Fung Kon Jin, P. H. P., Dijkgraaf, M. G. W., Alons, C. L., Van Kuijk, C., Beenen, L. F. M., Koole, G. M., & Goslings, J. C. 2011. Improving CT scan capabilities with a new trauma workflow concept: Simulation of hospital logistics using different CT scanner scenarios. *European Journal of Radiology*, 80(2), 504–509. <https://doi.org/10.1016/j.ejrad.2009.11.026>
- Gahan, J. 2010. Observational study of the capacity and demand of plain-film workflow in a radiology department. *Radiography*, 16(3), 182–188. <https://doi.org/10.1016/j.radi.2010.01.004>
- Huang, Y.-L., & Marcak, J. 2013. Radiology scheduling with consideration of patient characteristics to improve patient access to care and medical resource utilization. *Health Systems*, 2(2), 93–102. <https://doi.org/10.1057/hs.2013.1>
- Kansagra, A. P., Liu, K., & Yu, J.-P. J. 2016. Disruption of Radiologist Workflow. <https://doi.org/10.1067/j.cpradiol.2015.05.006>
- Lakdawalla, D. N., Bhattacharya, J., & Goldman, D. P. 2004. Are The Young Becoming More Disabled? *Health Affairs*, 23(1), 168–176. <https://doi.org/10.1377/hlthaff.23.1.168>
- Liker, J. K. 2003. The 14 Principles of the Toyota Way : An Executive Summary of the. *The 14 Principles of the Toyota Way : An Executive Summary of The*, 35–41.
- Lu, L., Li, J., & Gisler, P. 2011. Improving financial performance by modeling and analysis of radiology procedure scheduling at a large community hospital. *Journal of Medical Systems*, 35(3), 299–307. <https://doi.org/10.1007/s10916-009-9366-6>
- Ng, D., Vail, G., Thomas, S., & Schmidt, N. 2010. Applying the Lean principles of the Toyota Production System to reduce wait times in the emergency department. *Canadian Journal of Emergency Medicine*. <https://doi.org/10.1623/pj.2010.1623> [pii]
- Oliva, R. 2002. Tradeoffs in responses to work pressure in the service industry. *IEEE Engineering Management Review*, 30(1), 53–62. <https://doi.org/10.1109/EMR.2002.1022405>
- Oliva, R., & Sterman, J. D. 2001. Cutting Corners and Working Overtime: Quality Erosion in the Service Industry. *Management Science*. <https://doi.org/10.1287/mnsc.47.7.894.9807>
- Pitman, A., Jones, D. N., Stuart, D., Lloydhope, K., Mallitt, K., & O'Rourke, P. 2009. The Royal Australian and New Zealand College of Radiologists (RANZCR) relative value unit workload model, its limitations and the evolution to a safety, quality and performance framework. *Journal of Medical Imaging and Radiation Oncology*, 53(5), 450–458. <https://doi.org/10.1111/j.1754-9485.2009.02094.x>
- R Core Team 2014. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>
- Rachuba, S., Knapp, K., Ashton, L., & Pitt, M. 2018. Streamlining pathways for minor injuries in emergency departments through radiographer-led discharge. *Operations Research for Health Care*, 19, 44–56. <https://doi.org/10.1016/j.orhc.2018.03.001>
- RCSI. 2011. Measuring Consultant Radiologist workload in Ireland : (March).
- Reinus, W. R., Enyan, A., Flanagan, P., Pim, B., Sallee, D. S., & Segrist, J. 2000. A proposed scheduling model to improve use of computed tomography facilities. *Journal of Medical Systems*, 24(2), 61–76. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/10895421>
- Sargent, R. G. 2013. Verification and validation of simulation models. *Journal of Simulation*, 7(1), 12–24. <https://doi.org/10.1057/jos.2012.20>
- Shukla, N., Keast, J. E., & Ceglarek, D. 2014. Improved workflow modelling using role activity diagram-based modelling with application to a radiology service case study. *Computer Methods and Programs in Biomedicine*, 116(3), 274–298. <https://doi.org/10.1016/j.cmpb.2014.05.005>
- Sterman, J. D. 2000. Business dynamics. System thinking and modeling for a complex world. *McGraw-Hill Education*. Boston: , (January 2000), 982 pp. [https://doi.org/10.1016/S0022-3913\(12\)00047-9](https://doi.org/10.1016/S0022-3913(12)00047-9)
- Sterman, J. D. 2011. Communicating climate change risks in a skeptical world. *Climatic Change*, 108(4), 811–826. <https://doi.org/10.1007/s10584-011-0189-3>
- Sturm, R., Ringel, J., Lakdawalla, D., Bhattacharya, J., Goldman, D., Hurd, M., ... Andreyeva, T. 2007. *Obesity and Disability: The Shape of Things to Come*. RAND Corporation. <https://doi.org/10.7249/RB9043-1>