Original Article

Prioritizing magnetic resonance (MR) radiology functions for virtual operations: a feasibility study

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Background: Virtualization in radiology presents a growing opportunity to improve the efficiency and lower the cost of care delivery. Furthermore, it may provide a means to manage staffing shortages, reduce burnout, and encourage employee development. In radiology, the feasibility to perform several non-patient-facing imaging procedure tasks remotely is explored. Virtualization of magnetic resonance imaging (MRI) exams is of specific interest as it typically involves a range of complex tasks, and inefficiencies can increase patient wait times (WTs) and reduce overall utilization.

Methods: To explore this, a computer simulation model is developed to approximate turn-around time (TAT) and patient WT while accounting for technologist expertise and workflow complexity. The model was validated against 1,618 magnetic resonance (MR) inpatient/ED exams. Using cognitive task analysis (CTA), complex MR functions are identified from a technologist perspective that may require a high-level of expertise and thus influence workflow durations.

Results: Virtualizing complex, non-patient-facing functions may reduce MR workflow duration by up to 15% and patient in-exam WT by up to 75% when utilizing expert technologists. For example, scans involving the abdomen and spine and addressing unreported implants benefit the most from experts and may be supported remotely.

Conclusions: Modifying the workflow of MRI exams by segmenting complex, non-patient facing functions to expert technologists within an organization or in a remote center is feasible as it improves efficiencies and results in a better patient experience. In addition, administration now has guidance on how to effectively deploy a highly-trained workforce in a virtual setting.

Keywords: Magnetic resonance imaging (MRI); virtual operations; discrete event simulation; cognitive task analysis (CTA)

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Introduction

Magnetic resonance imaging (MRI) is an important diagnostic scanning tool for the detection and monitoring of specific diseases and conditions. However, equipment, operations, maintenance, and personnel (e.g., MR technologists) make the diagnostic tool expensive so improving workflow efficiency is valuable. Traditionally, telemedicine in radiology focuses on the electronic transmission of images and radiological reports for image interpretations (1,2). However, the processes in the MRI workflow can be improved as advances in computer and communications technology enable users better tools

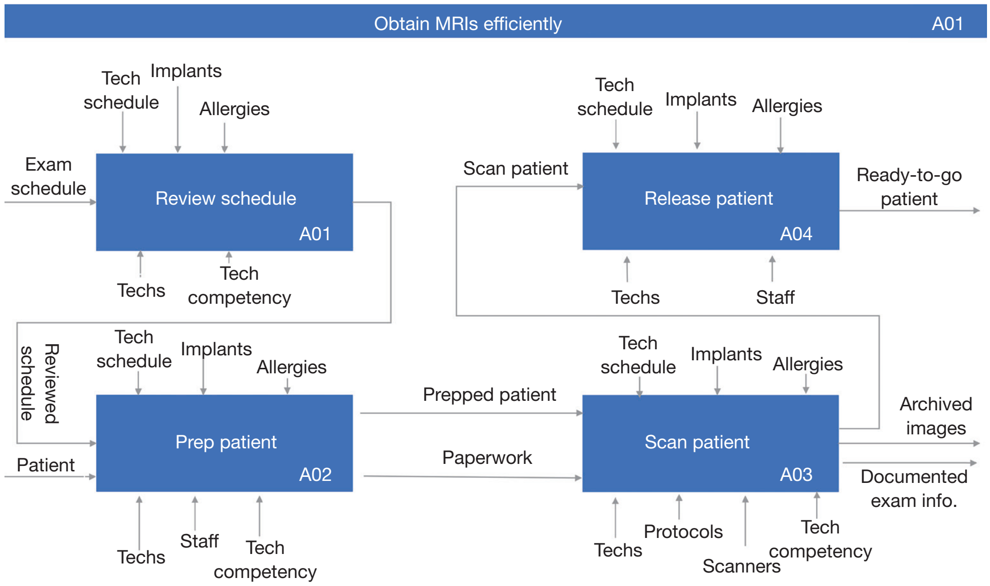

Figure 1 Highest level SADT diagram of MR image acquisition functions. MRI, magnetic resonance imaging; SADT, structured analysis and design technique; MR, magnetic resonance.

for the comprehensive exchange of information in real time. This research studies improvements in MR imaging processes using expert technologists to alleviate workflow constrictions. In addition, image acquisition tasks, that may be performed in a virtual environment, are also identified and the efficiencies of acquiring MRI exams evaluated. In this paper, virtual indicates work that may be performed in a remote operating center by a group of highly skilled technologists. We present the following article in accordance with the SQUIRE 2.0 reporting checklist (available at https://jhmhp.amegroups.com/article/view/10.21037/jhmhp-21-92/rc).

The hierarchical structure of the MR imaging functions is shown at the highest level in *Figure 1* and is depicted using an SADT (Structured Analysis and Design Technique) format (3). The functions given in this section are the foundational elements of the modeling that is discussed in the next section. The first function, Review Schedule, occurs up to 3 weeks in advance of an appointment. The function reviews the exam parameters for exam code, exam protocol and sedation/anesthesia orders and then the patient's record for allergies, body habitus, mobility needs, implants and other special needs. The Prep Patient function (A02) is performed by both technologists and medical assistants. The function begins with confirming arrival and patient identification in the electronic health record (EHR) then clearing implants that were not reported at the time the appointment was made, assigning lockers for patient changing, starting an IV or other port access, handling special needs (i.e., pacemaker, claustrophobia) and conducting final verification before walking the patient to the scanning room. The Release Patient function (A04) begins when the patient leaves the scanning room and ends after the patient changes, receives post-exam instructions and has any ports removed.

Figure 2 and *Figure 3* show the next level of functional decomposition which involves all activities that may affect image quality for the Prep Patient (A02) and the Scan Patient (A03) functions, respectively. Each top-level function, A01–A04, shown in *Figure 1* was decomposed two additional levels to fully capture the MR workflow; however, Prep Patient (A02) and Scan Patient (A03) functions are only given here because they are most relevant to the discussion herein. The Prep Patient function starts with identifying and screening the patient which involves asking about the patient's past medical treatments and procedures that may pose risks to patient safety during the MR exam (including but not limited to implants, surgical incisions, etc.). If an implant that is not reported in the patient's record surfaces in the screening process, the details about the implant will need to be obtained and addressed by a knowledgeable technologist to have it cleared; otherwise, the patient will be assigned a bay and a locker and change into the proper attire. If the patient needs an

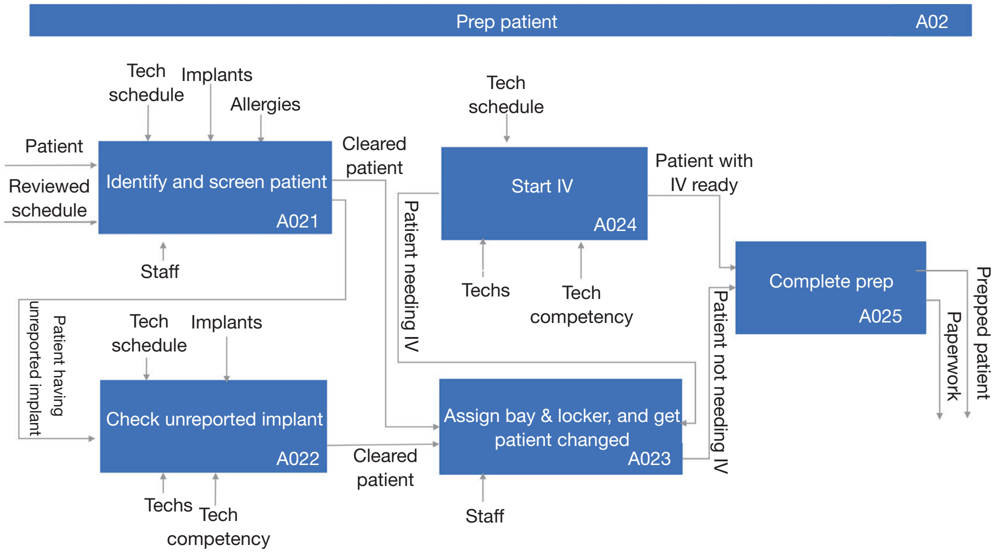

Figure 2 SADT diagram of Prep Patient sub-functions. SADT, structured analysis and design technique.

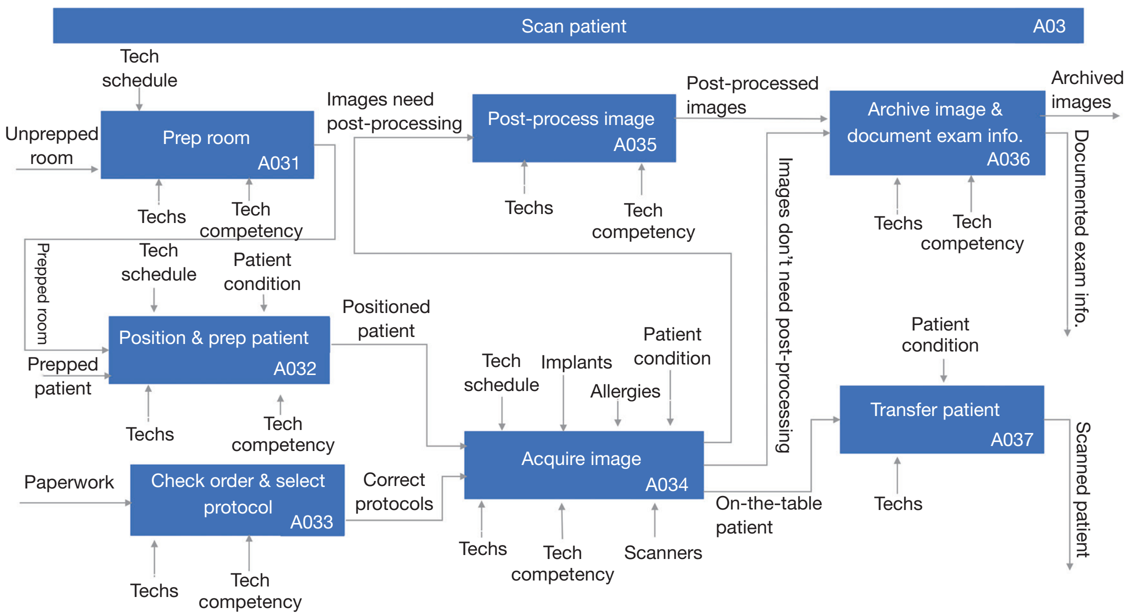

Figure 3 SADT diagram of Scan Patient sub-functions. SADT, structured analysis and design technique.

IV as suggested by the exam code, then after changing, an IV will be started. Prep Room includes preparing the coils and positioning devices as well as performing a last safety screening. Proper positioning of the patient ensures good images as well as patient safety and comfort. While the Review Schedule function has already occurred, there may be last-minute updates, so the order is reviewed and the protocol is selected from the MR scanner. The protocol may be updated with additional sequences at that point to ensure that the anatomy is fully scanned. As the protocol sequences are run in the Acquire Image function (A034), the technologist is continually monitoring the quality of the images. Some images, such as spectroscopy and angiograms, require post-processing before being sent to the picture archiving and communication system (PACS). Finally, exam details for billing are entered while the patient is escorted

Table 1 Mean and standard deviation of scanner time by anatomy (minutes)

	Brain	Head	Liver	Abdomen	Spine	Knee	Heart	Other (arm, heart, prostate, etc.)
Mean	39.1	34.81	37.4	40.05	44.72	35.59	75.20	–
SD	15.7	12.53	14.85	15.29	23.22	15.5	23.01	–
% of all exams	28%	18%	13%	13%	11%	5.9%	5.9%	5.2%

SD, standard deviation.

back to the changing bay and released.

After a baseline simulation model that represents the traditional MR workflow is developed and validated, two expert-usage scenarios are analyzed. Turn-around time (TAT) and wait time (WT) associated with the two expert-usage scenarios decrease across all modeled MR functions and patient attributes when compared to the baseline model. These findings are extended to explore workflow virtualization for a remote operating center that will not only increase efficiency but has the potential to increase patient access, workforce development and care standardization.

The next section of this paper presents the data sources of this study and explains the methods used to model traditional MR workflow and technologist expertise, the analyses that are conducted, and validation of the baseline model. The "Results" section describes the results of the baseline model and the expert-usage scenarios. An example is given which shows the benefits of using experts. Results of statistical analysis of different scenarios are also given in this section. The last section discusses the results and implications they have.

Methods

Opportunities for virtual operations reside with tasks that are most demanding in the MR workflow. A cognitive task analysis (CTA) is conducted to identify those demanding MR activities. Based on the findings of the CTA, a discrete-event simulation (DES) model is developed and used to explore different expert-usage scenarios.

Data sources

The data used in this study come from two sources: observations and scanner log files. Over 180 hours of observation were spent in the MR operations area conducting the CTA, characterizing the operations for functional decomposition, and gathering metric data for the functional tasks. Logfile data consisting of 68 variables on about 114K exams is utilized for scan time duration by anatomy, number of exams by exam type, and patient characteristics (i.e., age, weight, gender). This study focused on the 7 anatomies that represent >95% of all out-patient diagnostic scans (*Table 1*). The scanner log file data in *Table 1* shows that scanner time mean and variability differ by anatomy so the anatomy of the patient being scanned needs to be accounted for. For simplicity, only the top five anatomies which still account for >80% of all out-patient diagnostic scans are modeled.

CTA: identification of demanding MR activities

Many of the functions described in *Figures 1-3* are complex and the durations of the functions will be impacted by the experience of the technologist. As such, the MR workflow first needs to be characterized from a cognitive perspective as opposed to behavioral-based task analysis. Applied cognitive task analysis (ACTA) is used to elicit and capture difficult cognitive elements, rationale for their difficulty and potential errors (4-6). *Figure 4* presents selected findings from the CTA that are considered "complicated" from a technologist's perspective, and these findings identify the need for capturing and modeling expertise (as discussed in detail in the subsequent section). The challenging cognitive elements are synthesized, associated with MR functions and represent expert activity in the simulation model of the workflow. Expert technologists are utilized in all functions except Release Patient (A04).

Modeling expert knowledge

For a given task, a technologist's completion time reflects a relative experience level. As expertise accrues, the time technologists spend on MR operational tasks tends to decrease (7). To model expert knowledge, task times are randomly sampled from designated probability distributions. Expert task time is not documented for any

Difficult cognitive element	Rationale	Potential errors
Knowing whether the exam codes and protocols are appropriate	Correct protocols need to be selected for the exam. Discrepancies arise in the comments from prescribing physicians, protocolling radiologists and schedulers and the protocols to be used	Missing Important information in the comment lines. Not discovering a conflict between the intent of the scan order and the scheduled exam
Obtaining implant & allergy information and scheduling the exam accordingly	Various implants exist and clearance is needed. The exam needs to be scheduled on the appropriate imaging machine	Failing to notice implant information may increase exam duration. Scheduling the exam on the wrong machine
Detecting that the patient has an unreported implant(s)	Patients fail to report an implant in the screening process Patients may lack knowledge of medical terminology	Failing to obtain information on unreported implants from patients may affect image quality or even damage the implants. Failing to clear implants may increase exam duration
Starting patient IV	Blood vessels may be hard to find	Failing to start an IV in two attempts (as per department policy)
Detecting mistakes or irrationalities in protocol and order	Extensive knowledge of human anatomy, pathology, and protocol, etc., is needed	Discovering the conflict during imaging or after post-processing increases exam duration
Planning images based on survey/previous scans to cover the pathology adequately	Parameters (e.g., FOV, # of slices, etc.) need to be set or adjusted to get the best view of the pathology on the images	Improperly setting the parameters to obtain the best images
Identifying the area(s) of interest for vague orders/protocols	Knowledge of human anatomy and disease pathology is needed to obtain images	Missing visibility of the pathology in the images
Identifying artifacts that cause poor image quality	Artifacts need to be detected and then controlled or eliminated	Not understanding the cause of the artifact
Modifying the exam card to obtain the best image (e.g., add/repeat sequences)	Technologist knowledge of imaging sequences is needed to modify the exam card	Repeating sequences or adding additional sequences increases scanning time
Positioning patients with special conditions/ needs	Technologists need to know how to use different positioning devices and switch coils when needed	Failing to position patients well may result in uncomfortable patients, images with motion or artifacts, unsafe patients

Figure 4 Selected findings from the cognitive task analysis by MR workflow function. Color denotes high-level function: Review schedule (A01), Prep patient (A02), Scan patient (A03). FOV, field of view; MR, magnetic resonance.

tasks in the MR workflow, so the triangular distribution as a subjective description of the population is used.

Two different classes of task time distributions are used in this study: the expert technologist task time distribution ("expert distribution" for short) and the average technologist task time distribution ("average distribution" for short). For any task, experts tend to have a smaller average task time and a smaller variability. It should be noted that historical data is not available for the expert distributions. In order to estimate these, the mode and the upper limit of the respective average distributions are decreased by a specific amount (assuming the lower limit stays the same). The percentage of the decrease is determined by findings in Weinger & Slagle (7) and verified by SMEs.

Discrete-event simulation (DES) model

DES has long been used to model health care systems (8-12). A DES model is developed and implemented using the SimPy package in Python (Version 3.8.3) (13,14). The key output metrics include TAT and WT. TAT is defined as the time from when a patient begins the identity confirmation and safety screening function (A021) to when the patient is returned to the changing area (A04). WT is the time that the patient is waiting for a resource such as a technologist, medical assistant or scanner; WT is included in the TAT.

For each simulation run, a pool of 500 patients is generated, and each patient is assigned five attributes: (I) habitus (normal, obese); (II) exam type (brain, head, liver, spine, abdomen); (III) implant (no implant, unreported implant, non-interfering implant, conditional pacemaker, non-conditional pacemaker); (IV) IV (needed, not needed); (V) allergy (yes, no). The frequency of occurrence of each attribute is determined by observation, log-file analysis and subject matter experts. These 5 anatomies occur most frequently and comprise approximately 80% of the MR exams. *Figure 5* shows how a simulated patient is represented and stored as a vector in the patient pool. The last row is an example patient who has a normal habitus, is having a scan related to the head, has no implants that need to be considered during the exam, needs an IV for contrast administration and has no known allergy (e.g., contrast reaction and/or claustrophobia). While claustrophobia is not an allergy, this field identifies conditions that will impact the scan; if a patient is claustrophobic, additional time (sampled from a Gaussian distribution) is added to task duration.

The patients in the pool are then "released" into the simulated MRI unit and move through each function

	Habitus	Exam type	Implant	IV	Allergy
Reactive	Normal 90%	Brain 34%	No implant 65%	Needed 80%	Yes 15%
Nonreactive	Obese 10%	Head 21%	Unreported implant 5%	Not needed 20%	No 85%
		Liver 16%	Non-interfering implant 20%		
		Abdomen 16%	Conditional pacemaker 5%		
		Spine 13%	Non-conditional pacemaker 5%		
Example patient	Normal	Head	No implant	Needed	No

Figure 5 Patient attributes and rate of occurrence in the simulation model.

(i.e., task) in the MR workflow sequentially. In the model, patients arrive at a fixed interval of 15 minutes. The simulation model contains 12 functions in total which are decomposed from the highest level functions shown in *Figure 1*. The functions include the four sub-functions (A021–A024) of Prep Patient, the seven sub-functions (A031–A037) of Scan Patient, and the function of Release Patient (A04). The model tracks state changes of the individual patient as well as other entities in the simulation model (e.g., technologists, scanners etc.). The simulation terminates when the last patient finishes their exam and is released. Functions, for example, that are not in the scope of the models include the functions related to scheduling, consent and safety screening, insurance pre-authorization, contrast administration and scanner exam assignment.

Baseline model validation

The baseline simulation model is validated against MR inpatient/ED TAT data collected between March 2019 and February 2020 at the academic facility where the study is conducted. Since inpatients and ED patients will usually have been prepped (i.e., implants identified, attire changed, IV started) by the time they show up at the MR unit, the data only includes time from when they enter the scanner room to the time they leave the room; this process is captured by the Scan Patient (A03) function in the simulation model, thus the simulated task time for Scan Patient is compared to the historical data for the purpose of model validation.

The data used for model validation requires elimination of duplicate records, infeasible exam records and concatenation of exam cards. Errors are also observed in the data: exams that have durations that are too short/long to be correct. For example, brain stroke scans (MRI BRAIN STROKE) that have a duration of 0 minutes and brain scans (MRI BRAIN WO/W CONT) that have a duration of 827 minutes are incorrect. To correct this, exams were grouped by exam code and then exams with durations that are below the 10th percentile or above the 90th percentile in the category are removed from the data. The validation data consists of 103 different exam codes; the majority of which occur infrequently. The top 14 most frequently occurring exam codes were retained and these represent approximately 80% of the total cases. Average durations by exam code are calculated, and the average duration across different exam codes are obtained as the weighted average.

Prior to cleaning, 2,931 exams comprise the data; after cleaning, 1,618 exams remain (446 exams were excluded due to duplication, 474 exams were excluded because the exam codes were not in this study, 393 exams were excluded due to unreasonable durations). The mean duration for the scan-patient function is 41.36 minutes and the mean duration for the simulation model scan-patient function is 46.70 minutes. The (μ+1σ) intervals on mean duration from historical inpatient data and the mean duration of scan patient function of the simulation model are (28.91, 53.81) and (37.04, 56.36), respectively. The difference is likely to be caused by a small difference in the types of exams between inpatients and outpatients. Taking these factors into consideration, the subject matter experts conclude that the simulation model output is in accordance with the historical data, and the simulation model is validated.

Analyses

Based on the validated baseline model and findings of the CTA, we explore opportunities for formalizing expert usage in the MR workflow as a precursor to workflow virtualization for remote operations and evaluate the impact of such expert usage on system metrics such as TAT and WT. Specifically, two expert-usage scenarios are identified

Table 2 Triangular distribution parameters for MR functions utilizing experts

Function	Average distribution			Expert distribution		
	Distribution parameters (minutes)	Mean	Std. Dev.	Distribution parameters (minutes)	Mean	Std. Dev.
Check unreported implant (A022)	(5, 7, 30)	14.00	5.67	(5, 6.3, 24)	11.77	4.33
Start IV (A024)	(3, 7, 20)	10.00	3.63	(3, 4.5, 16)	7.83	2.90
Prep room (A031)	(2, 3, 4.5)	3.17	0.51	(2, 2.7, 3.6)	2.77	0.33
Position & prep patient (A032)	(2.1, 3.9, 5.2)	3.73	0.64	(2.1, 3.5, 4.2)	3.27	0.44
Check order & select protocol (A033)	(0.5, 0.8, 1.3)	0.87	0.16	(0.5, 0.7, 1)	0.73	0.10
Acquire image (A034)	Brain: (20, 35, 40); Head: (23, 35, 48); Liver: (30, 40, 55); Spine: (22, 45, 67); Abdm: (25, 40, 55)	Brain: 31.67; Head: 35.33; Liver: 41.67; Spine: 44.67; Abdm: 40.00	Brain: 4.25; Head: 5.11; Liver: 5.14; Spine: 9.19; Abdm: 6.12	Brain: (20, 31.5, 32); Head: (23, 31.5, 38.5); Liver: (30, 36, 44); Spine: (20, 40.5, 60.3); Abdm: (25, 36, 44)	Brain: 27.83; Head: 31.00; Liver: 36.67; Spine: 40.27; Abdm: 35.00	Brain: 2.77; Head: 3.17; Liver: 2.87; Spine: 8.23; Abdm: 3.89
Post-process image (A035)	(4.5, 6, 8)	6.17	0.72	(4.5, 5.4, 6.4)	5.43	0.39

MR, magnetic resonance; Std. Dev., standard deviation; Abdm, abdomen.

and examined, whose performance is then compared to the baseline model given in the "Results" section which represents the traditional MR workflow. *Table 2* shows the functions that may require expert help as a result of the CTA and thus have both an average distribution and an expert distribution. Weinger & Slagle (7) found that for a specific task, expert anesthesiologists may spend up to 50% less time than novice anesthesiologists. Since the MR technologists observed were not complete novices, a task time reduction well below 50% is assumed. Specifically, the mode is decreased by 10% and the upper limit by 20% in an expert distribution, compared to those of the average distribution. The values in *Table 2* are used in modeling each scenario.

The first scenario studied is an *All-Expert-Onsite* scenario, where all tasks in the workflow that would benefit from increased capability are performed onsite by expert personnel only. Such tasks include check unreported implant (A022), start IV (A024), prep room (A031), position and prep patient (A032), check order and select protocol (A033), acquire image (A034), and post-process image (A035). In this model all the task durations are randomly drawn from only the expert distributions shown in *Table 2*. This scenario effectively represents a bound for system performance; that is, it represents the shortest potential TAT and WT.

The second scenario studied is a *Remote-Technologist* scenario, which moves towards virtualization by offloading the non-patient-facing tasks to a remote location staffed exclusively by experts. Only non-patient-facing tasks are considered for offloading because although expert help may be needed for some tasks, they cannot be effectively assisted in a virtual environment. For example, Start IV is a function where expert help may be needed because some patients have blood vessels that are hard to find. Policy states that the same person shall not stick a patient more than two times without success; therefore, in cases of a difficult IV, an expert technologist or nurse may be called in for help. However, this is not a task that can be virtualized, since it requires face-to-face interaction with patients. Functions that do not require direct contact with patients include check unreported implant (A022), check order and select protocol (A033), acquire image (A034) and post-process image (A035) and are opportunities for virtualization. The remaining functions in *Table 2* require direct contact with patients or have to be performed locally. This scenario represents a situation where a local site could be administered by medical assistants and/or nurses, and a remote site could be structured to support multiple local sites.

Statistical analysis

All statistical analyses were done in the R language using

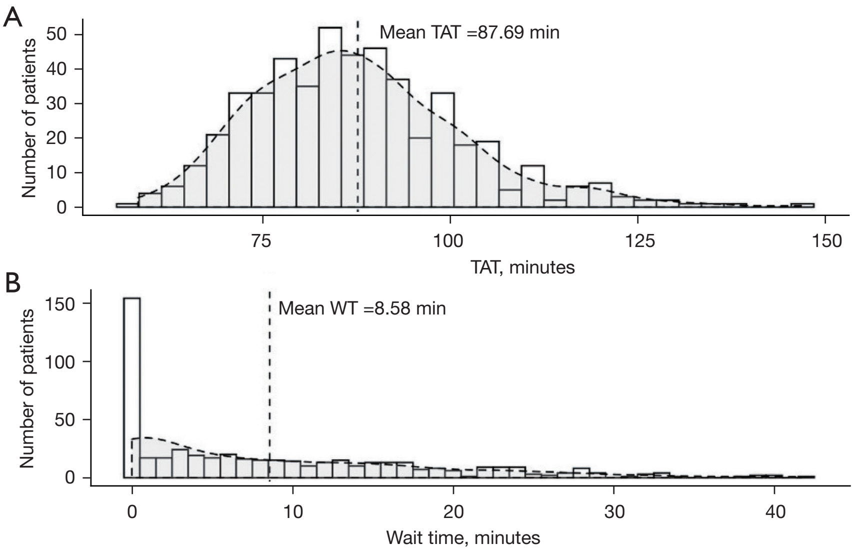

Figure 6 Baseline simulation model results (one simulation run): (A) TAT (minutes); (B) WT (minutes). TAT, turn-around time; WT, wait time.

Table 3 Results of the baseline model

	Mean TAT (minutes)	Mean WT (minutes)
Baseline model	87.69 (1.45)	8.58 (1.27)

The standard deviation of the mean is given in ().TAT, turn-around time; WT, wait time.

RStudio (Version 1.1.456).

Results

Baseline model result

Figure 6A shows the distribution of TATs for 500 simulated patients from one simulation run; *Figure 6B* shows the distribution of WTs for the same 500 simulated patients. The baseline model is replicated 30 times and the mean TAT and mean WT over the 30 simulation runs are shown in *Table 3*.

The baseline model provides insights into the patient attributes. *Figure* 7 shows that exam type (*Figure 7B*) and implant status (*Figure 7E*) tend to affect exam duration while patient habitus, patient allergies and IV requirements do not. Exam type and implant status are further explored. *Figure 8* shows that patient characteristics do not significantly affect WTs. MR exam durations vary by anatomy but utilizing experts may reduce longer scan times and reduce TAT. In addition, improving implant knowledge may also reduce TAT. Note that each plotted point is the mean TAT from one replication of the baseline model.

Expert-usage scenario result

Each of the expert models is replicated 30 times, and the results are shown in *Table 4*. Under all scenarios, the use of expert technologists reduces TAT and WT. By simply offloading the non-patient-facing functions to expert technologists in the remote-technologist model, the average TAT per exam is reduced up to 12.54 minutes and the average WT is reduced up to 6.44 minutes when compared to current operations where expert help is provided on an informal basis. Note that the remote-technologist model has a comparatively longer TAT and WT because only the non-patient-facing functions are studied. In other words, this model only utilizes durations from four expert distributions, whereas the all-expert-onsite model uses durations drawn only from the expert distributions.

An example

While the all-expert-onsite model represents an idealized situation where all tasks are performed by experts, a more realistic situation is that experts are “tapped” on an informal basis when needed. Moreover, it is assumed in this example that the expert workload comprises both scheduled and on-

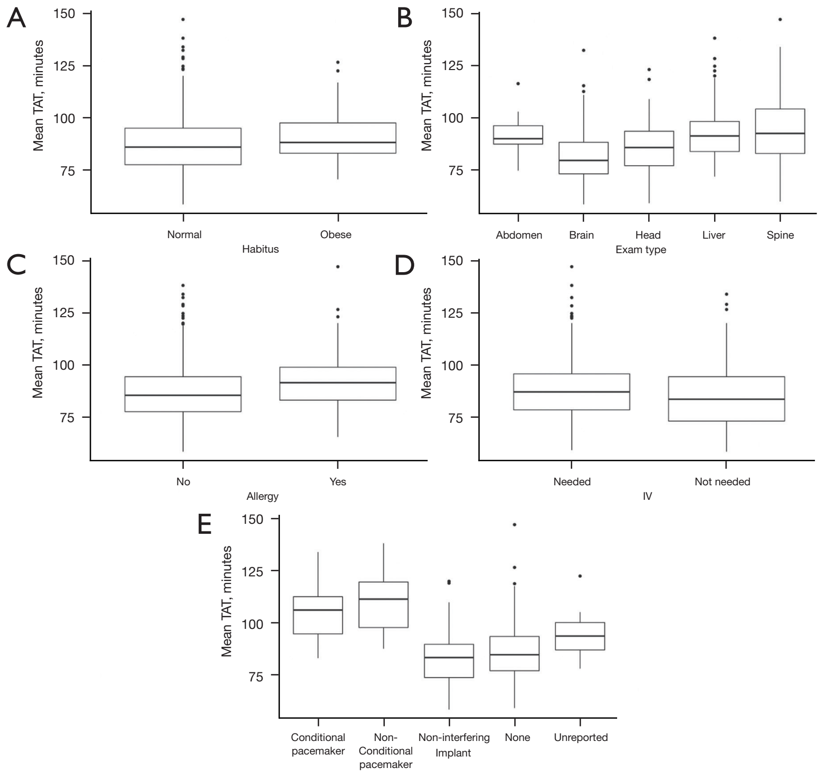

Figure 7 TAT by patient attributes for baseline model: (A) habitus; (B) exam type; (C) allergy; (D) IV; (E) implant. TAT, turn-around time.

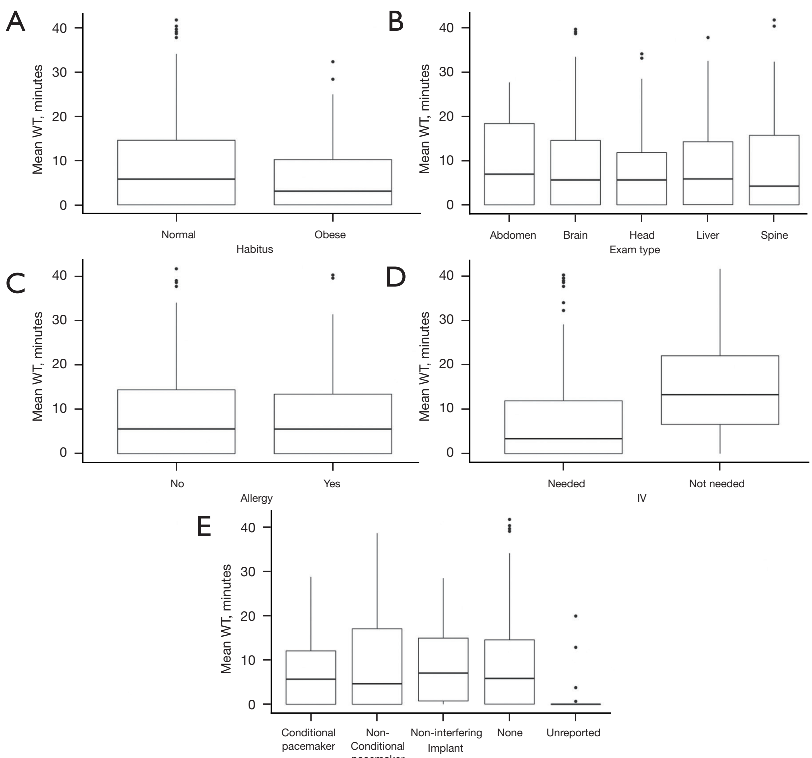

Figure 8 WT by patient attributes for baseline model: (A) habitus; (B) exam type; (C) allergy; (D) IV; (E) implant. WT, wait time.

demand components. The scheduled workload includes exams that are known to be difficult to perform for the less experienced technologists, and the on-demand workload includes impromptu requests for help.

Note that abdomen and spine exams have longer image acquisition durations and/or variability, and are generally perceived as more challenging by MR technologists, Therefore, in this example, when these exams are on the schedule, they are routed to a remote operations center staffed by expert technologists. Since unreported implants require evaluation by an expert technologist, they are also be routed to the remote operations center; this represents an unscheduled or on-demand workload for the technologist. *Table 4* (bottom row) shows the metrics for this example: offloading more complex exams and potentially risky implant situations reduces TAT and WT when compared to the current operations (i.e., baseline model).

Table 4 Simulation results of baseline and expert models

Models	Mean TAT (min)	Mean WT (min)
Baseline model	87.69 (1.45)	8.58 (1.27)
All-expert-onsite model	71.59 (0.40)	1.25 (0.20)
Remote-technologist model	75.15 (0.46)	2.14 (0.28)
Example (ABD, SPN, unreported implant)	83.62 (0.81)	5.54 (0.65)

The standard deviation is given in (). TAT, turn-around time; WT, wait time; ABD, abdomen; SPN, spine.

Comparison

Pairwise *t*-tests are used to determine if statistically significant differences exist between the mean TAT and mean WT of all three models: the baseline model and the two expert models. The box plots in *Figure 9A* represent the mean TAT for each model and the stars above the horizontal lines denote the level of significance for each of the 3 pairwise comparisons—all of which are significantly different. *Figure 9B* plots the same information for mean WT. Again, all pairwise comparisons are significant. The findings suggest that by having experts in the workflow, efficiency gains and reductions in variability can be achieved. What's more, the higher the expert involvement, the more efficiency gains are realized. While the remote-technologist model does have longer TAT and WTs than the all-expert-onsite model, the efficiency gains are substantial compared to the current workflow.

Discussion

Teleradiology is typically associated with the electronic transmission and processing of radiological images; however, advances in communication technology can support more efficient and reliable exchange of information in real time that is distinct from MR scanner technology. At the same time, healthcare is shifting toward a value-based care model. While the concept of value-based care is being defined and aligned, virtualizing MR image acquisition

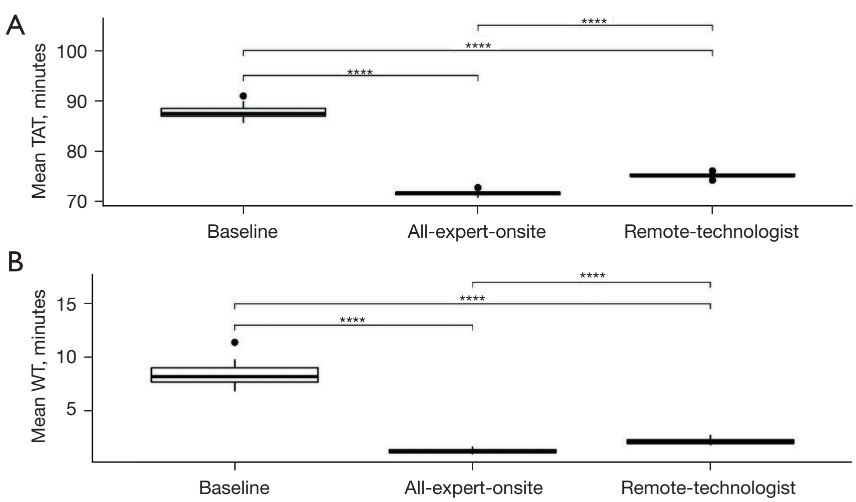

Figure 9 Pairwise comparison of mean TAT and mean WT of different models: (A) mean TAT (minutes); (B) mean WT (minutes). ****, P<0.001. TAT, turn-around time; WT, wait time.

can increase value by optimizing workflow, improving staff efficiency and providing an opportunity for workforce development.

In this paper, the activities in an MR workflow were analyzed from the competency perspective of a technologist, and functions with increased cognitive demand were identified. These functions represent opportunities for improved efficiencies by utilizing experts to complete them. Using DES, two expert models were explored. Results show that by just offloading the functions of 'checking unreported implants' and 'acquiring image' to expert technologists, the average TAT per exam is reduced up to 12.54 minutes and the average waiting time is reduced up to 6.44 minutes when compared to the traditional MR workflow which includes the situation where expert help is provided on an informal basis.

Since these key functions do not require patient interaction, they are suitable for virtualization. The findings indicate that using experts in a remote capacity is feasible as efficiency is significantly improved. In addition, using experts in a virtual environment has other benefits:

(I) Increased utilization of scanners. Expert technologists would have the ability to support multiple imaging rooms which may include scanners/sites that are underutilized in rural areas, for example;

(II) Improved patient experience. Expert technologists are a shared asset in a network so patients may not need to travel to another location to receive access to high-quality care;

(III) Continued workforce development. Developing expert technologists provides a path to recognition, continues competency development, and increases job satisfaction;

(IV) Increased care standardization. A remote center staffed with expert technologists enables the same high level of image quality, protocol, and diagnostic outcomes in a rural setting as well as an academic medical center.

The limitations of this work lie in what was not studied. While the anatomies, exam codes, technologist and MA functions, and workflow processes included in this work represent more than 80% of the MR imaging acquisition workload, there could be a bias that results from the exams not included. In addition, the study site is typical of large academic medical centers and may not reflect small radiology clinics or diagnostic imaging chains. However, the use of discrete event simulation as the underlying modeling mechanism provides generalizability for use in not only MR image acquisition but other healthcare delivery workflows where expert knowledge affects process times and where virtual operations may be considered.

Advancements made in virtual operations not only contribute to faster TATs and a better patient experience, but also help increase overall productivity of MR departments while providing more operational sustainability. A remote site composed of expert technologists warrants further work in the areas of assessing and characterizing technologist competency, balancing image acquisition tasks with cognitive load in a virtual environment to maintain expert resiliency and capacity and understanding the impact of task handoff between on-site and virtual locations on patient safety.

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