Balancing Clinical Experience in Outpatient Residency Training

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Background. To receive adequate training experience, resident panels in teaching clinics must have a sufficiently diverse patient case-mix. However, case-mix can differ from one resident panel to another, resulting in inconsistent training. Method. Encounter data from primary care residency clinics at Massachusetts General Hospital from July 2008 to May 2010 (64 residents and ~3800 patients) were used to characterize patients by gender, age, major disease category (both acute and chronic, e.g., Cardio Acute, Cardio Chronic, etc., for a total of 44 disease categories), and number of disease categories. Imbalance across resident panels was characterized by the standard deviation for disease category, patient panel size, and annual visit frequency. To balance case-mix in resident panels, patient reassignment algorithms were proposed. First, patients were sorted by complexity; then patients were allocated sequentially to the panel with the least overall complexity. Patient reassignment across resident panels was considered under 3 scenarios: 1) within preceptor, 2) within a group of preceptors, and 3) across the entire practice annually. Results were compared with case-mix (pre-July 2012) and post-July 2012. Results. All 3 reassignment algorithms produced significant reductions in standard deviation of either number of disease categories or diagnoses across residents when compared with baseline (pre-July 2012) and actual July 2012 reassignment. Reassignment across the clinic and group provided the best and second best scenarios, respectively, although both came at the cost of initially reduced patient-preceptor continuity. Conclusion. Systematically reallocating patient panels in teaching clinics potentially can improve the consistency and breadth of the educational experience. The method in principle can be extended to any target of health care system reform where there is patient or clinician turnover. Key words: patient panels, access to care, continuity, resident training, education.

Teaching clinics must provide a quality training experience to their residents. This requires residents to have consistent exposure to a range of clinical experiences from which to learn, along with easy access to their preceptors. The distribution of types of patients (age, gender, etc.), the range and frequency of clinical problems within these patients, the number of patients with specific types of problems/learning opportunities, and the absolute number of patients for whom a resident is responsible (panel size) directly influence the range of experiences available during training.

During their 3-year training, each medicine resident manages a panel of patients. Typically, each resident also works closely with 1 preceptor for the 3-year duration. Each preceptor supervises 3 or 4 residents, whom the preceptor typically does not share with other preceptors. Patients in the resident panels also belong to the preceptor’s panel for which they provide backup continuity; preceptor panels therefore are larger. When a patient from the panel visits the clinic, she may see both the resident and the preceptor. In addition, as part of the training/education process, the resident may have a conversation about the patient with the preceptor. A patient in a panel is likely to request an office visit multiple times each year; thus, there is value in maintaining continuity.
Every year, one-third of residents in training programs graduate and their patients must be reassigned to panels of new incoming residents. At present the annual reallocation process is performed in either an ad hoc way or by using the best judgment of clinic leadership. As a result, resident panels often differ substantially in case-mix, resulting in an inconsistent training experience. More complex patients are likely to demand a higher visit frequency, often overwhelming available scheduling capacity and adversely affecting timely access to care (wait time for appointments) and patient-clinician continuity.9

We set out to develop a framework for systematically optimizing patient reassignment at the beginning of an academic year (when a natural reallocation opportunity presents itself) so as to balance the range of clinical experiences to which resident are exposed during their training. We designed a computer algorithm that sorts patient panels by weighting factor(s) of interest, for example, age, gender, and complexity (number of and type of diagnoses within a single patient). The algorithm assigns each patient in sequence, iteratively allocating the current most complex (or other mixed weight measure) patient to the clinician with least complex patient panel. This is similar in principle to longest-task-first sorting algorithms, which have been shown to produce near-optimal solutions. In this article, we discuss the framework and the projected results of this process for a primary care internal medicine residency clinic at Massachusetts General Hospital (MGH).

METHODS

Data Description

We collected encounter data from primary care residency clinics affiliated with MGH over a 21-month period (1 July 2008 to 30 April 2010). The total set of trainee practices consisted of 258 residents and approximately 17,000 patients who visited over that time. For an initial analysis we grouped patients by gender and age, which was further subdivided into 10-year increments. These classifications were chosen as preliminary parameters to determine frequency demographics and the dependency that patient visits may have with regard to age and gender. The largest resident clinic in this sample, with 64 residents (~3800 patients), was chosen to be examined before and after real-world reallocation as it had the most real-world reallocation opportunities within resident, preceptor, and pod (preceptor group).

Measures of Panel Case-Mix and Complexity

We use 2 different measures to quantify case-mix in resident panels—diagnosis mix and diagnoses span.

Diagnosis mix. To characterize case-mix and complexity within each resident’s panel, we first determined the mix of diagnoses in each resident’s panel. This was done using the diagnosis codes associated with patient visits. Diagnosis codes were grouped by major disease category, both acute and chronic. Examples of major disease categories included are Neuro Acute, Neuro Chronic, and Cardio Acute, Cardio Chronic. In all there were 44 disease categories.

Diagnoses span. Individual patients may contribute more than 1 diagnosis to a patient panel, and a single patient’s set of diagnoses may fall across several different disease categories. For example, 1 patient may have 5 diagnoses that are all cardiovascular acute diagnoses; another patient may also have 5 diagnoses, but 2 may fall under psychiatric, 2 under cardiovascular chronic, and 1 neurological acute. The former patient spans only 1 major disease category, while the latter patient spans 3 major disease categories.

Therefore, another way of capturing case-mix is to count the number of patients whose diagnoses fall in k disease categories, where k can take on any value from 1 to 44 (the total number of disease categories). Table 1 provides an example of case-mix by number of patients whose diagnoses span k disease categories. The value of k therefore can be used as a proxy for patient complexity; patients who span a large number of diseases are considered more complex.

Standard Deviation as a Measure of Imbalance

The imbalance or nonuniformity across residents was quantified by using standard deviation (STD) measures. For example, if there are 4 residents and the total number of diagnoses (across all disease categories) in their panels is 127, 244, 145, and 169, respectively, then the imbalance is simply the standard deviation of these 4 numbers, 51.46 (standard deviation for diagnoses = STD_DIAG). The higher the STD_DIAG, the more unequal the diagnosis exposure rate. This same calculation can be carried out across preceptors who supervise sets of residents or any other relevant grouping.

Patient Reassignment Algorithms

Our algorithms can be broadly classified into those using diagnosis count and those using diagnostic category span.
The algorithm is executed in 2 parts. First, patients are sorted in decreasing order of the number of diagnoses or category span associated with each patient. Initially, the resident panels are empty. In the second part, patients are assigned 1 at a time to the panel with the smallest count of diagnoses; that is, the next most complex patient on the list is assigned to the resident who has the smallest count of number of diagnoses.

We try to maintain the resident-patient link as much as possible so long as it does not affect the standard deviation measure. Suppose that the resident to whom the next patient is to be assigned to maintain uniformity in panels is Resident 1. Suppose also that Patient 1 and Patient 2 are the first and second on the sorted list and they both have the same complexity and that Patient 2 belongs to Resident 1’s panel while Patient 1 currently belongs to some other resident’s panel.

Then it does not make sense to assign Patient 1 to Resident 1 when Patient 2 has the same complexity and already belongs to Resident 1. So our algorithm would “assign” Patient 2 to Resident 1, thus keeping the current link between the resident and the patient but also ensuring that the uniformity measure across panels is unaffected. This is an example where multiple equivalent solutions were possible. From a pure panel uniformity perspective, assigning Patient 1 to Resident 1 would also be optimal, but we wanted avoid breaking existing links when possible.

In case there is no obvious tiebreaker as described above, patients are allocated according to the next highest priority criterion, such as panel size.

The patient reassignment algorithms—one that uses diagnosis mix and one that uses diagnoses span—are applied at 4 different “levels,” where a level refers to the number of residents involved (resident group size) in the reassignment. We start with the smallest level and proceed until the level covers all residents in the clinic:

1. Restricted Reassignment (RR): In this case, only patients of graduating residents are reassigned incoming residents, while ensuring that such a reassignment happens only within a particular preceptor. This is the most restricted version of the reassignment and may not adequately address the issue of imbalances across resident panels, but it ensures that patient-preceptor link is maintained and patient handovers are logistically feasible.

2. Reassignment Within Preceptor (RWP): Here patient reassignment is applied to patients of all residents within a preceptor, including those residents who are not graduating. No patients are reassigned across preceptors, and patients maintain continuity with the preceptor.

Table 1  

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Note: CVS, cardiovascular; GI = gastrointestinal; ID, infectious disease; O/G, obstetrics/gynecology; IMA = Internal Medicine Associates; Res = resident.

This truncated table illustrates the case-mix for a sample of 64 IMA residents based on a sample of acute and chronic major disease categories. For example, Resident 1 has 73 patients total in her panel. These patients contributed to 40 CVS acute diagnoses and 34 Psych Chronic diagnoses. The mean number of diagnoses under each major disease category is also provided. The standard deviation (STD) of diagnoses counts under each category is also provided. For example, STD_CVS (CVS Acute) is 6.96, and STD_PsychC (Psych Chronic) is 5.79. These standard deviations are a measure of nonuniformity—and thereby inconsistency in resident training—across residents for a particular disease category. The complete table has been truncated for clarity. The full table is available on request.
3. Reassignment Within Group (RWG): Patients are reassigned for all residents within a group of preceptors. The motivation behind using RWG is that with a larger pool of patients, residents, and preceptors there are more opportunities to balance patient complexity for each resident panel, but with RWG there is a potential tradeoff with less preceptor-patient continuity.

4. Reassignment Across Clinic (RAC): This represents the case where a clinic chooses a complete panel redesign to minimize the imbalances across panels. RAC should allow the practices the greatest opportunity to correct imbalances since the larger the pool of patients, the greater the likelihood of diverse diagnoses. This comes at the potential cost of loss of patient-preceptor continuity.

Predicting Reallocation Performance

We tested the potential impact of these 8 algorithms (4 levels for the diagnosis mix algorithm plus 4 levels for diagnoses span algorithm) in a real-world setting using patient panel data from the 64 residents with 3800 panel patients assigned to 17 preceptors at an MGH outpatient clinic named IMA (Internal Medicine Associates) for the year 2011–2012, before (Original/Baseline) and after the July resident turnover (Actual). Our method, however, is applicable to any number of residents and for any number of patients.

RESULTS

Patient demographics and visit variation are shown in Figure 1:

Table 1 shows the case-mix for the 64 residents based on acute and chronic major disease categories. In this sample, Resident 1 has 73 total patients in her panel. These patients contributed to 40 CVS Acute diagnoses and 34 Psych Chronic diagnoses. The mean number of diagnoses under each major disease category and standard deviation within category are provided. For example, STD_CVSA (CVS Acute) is 6.96, and STD_PsychC (Psych Chronic) is 5.79. These standard deviations are a measure of nonuniformity—and thereby potential inconsistency in resident training—across residents for a particular disease category.

Table 2 shows case-mix as function of the number of patients who span $k$ major disease categories for the same residents in Table 1. The value of $k$ is used as a proxy for patient complexity; a larger disease span implies more complex patients. Here, for brevity, $k$ ranges from 1 to 20. For example, there are 7 patients in Resident 5’s panel whose diagnoses fall in 8 different major disease categories; in contrast, Resident 4 has only 2 such patients. Standard deviations for a particular $k$ reflect nonuniformity in patient complexity across resident panels. The standard deviations for $k = 11, 12, 13$ are the highest, indicating that this sample of residents differs significantly at those complexity levels.

Figure 2 shows the standard deviation of the number of diagnoses in the major disease categories across all 64 residents for the different reassignment methods. The major disease categories that have the greatest standard deviation in the variation across residents are shown from left to right on the x-axis. Note how RWP, RWG, and RAC have lower standard deviations compared with the baseline (original, before July 2012) and actual (July 2012 reassignment) as well as the restricted reassignment (RR).

Figure 3 shows the standard deviation of number of patients who span $k$ major disease categories across all 64 residents. Standard deviation peaks from $k = 8$ to $k = 15$, suggesting that nonuniformity in resident panels is greatest at these levels of patient complexity. As in Figure 2, RWP, RWG, and RAC perform better than baseline and actual.

Figure 4 shows the standard deviation in the panel patient numbers and average annual visits for the 64 IMA residents. The trends remain as before. Note that RAC reduces to near zero the variation in both panel sizes and visits.

DISCUSSION

Systematically reorganizing patient panels can substantially improve the range of educational experiences for trainees over the current state of affairs. An algorithmic approach works best when patients are most free to move between providers. For example, if everyone was free to be reassigned, consistency in educational exposure would be the best possible. However, this degree of reassignment is usually not achievable, certainly not in a single step, for logistic, organizational, and political reasons. Fortunately, constraining reassignments to within clinical teams and groups achieves much of the same aims, minimizes loss of continuity, and is likely more acceptable for all patient, clinician, and organizational stakeholders. This is particularly relevant since this result is consistent with the current movement toward group practices and medical homes.10–12 In
addition, reassigning within groups has the added advantage of preserving matching on unobserved variables that may have been driving selection for the base case groups in the first place, such as unspecified patient preferences, geography, and insurance.

In reassigning patients, careful attention needs to be paid to handovers, especially for patients with complex conditions. In a direct handover—when an incoming resident takes on the care of a patient from a graduating resident—a conversation is necessary between the graduating and incoming resident. The preceptor may also need to be involved. If patients of a graduating resident are being assigned to multiple incoming residents (this would depend on whether the reassignment happens within preceptor, group of preceptors, or the entire clinic), handovers for complex patients would involve coordination at multiple levels. For instance, the graduating resident may need to speak to 2 or more incoming residents, and perhaps more than 1 preceptor may be involved in the discussion. Such handovers need to be planned in advance, and

Figure 1  (a) Demographics and visits by age. (b) Demographics and visits by gender.
adequate time needs to be included in resident and preceptor schedules. Our algorithms assume that reassignments happen instantly at the time of arrival of the new incoming residents. However, in practice, assignments can be implemented in an incremental manner and can be staggered over the months leading up to the end of the fiscal year, an experiment we are currently launching. An interesting direction for future work is to determine the number of years it would take to realize the full benefits of reassignment given the constraints on the number of handovers that can be effectively coordinated each year.

Reassignment certainly comes with a short-term disruption in continuity, which can be mitigated as discussed above. However, in the long term, panels that are balanced in their case-mix are likely to be able to better maintain continuity. Two previous papers, using simulation and stochastic optimization methods applied to Mayo Clinic primary care data, show that panels with identical case-mixes will result in higher levels of continuity and access compared with panels with imbalance in workloads. When panels are imbalanced (i.e., when some panels have more complex patients with greater care needs than others), the probability that patient requests exceed the available capacity of the overburdened providers is high. Thus, many patients either will have to wait to see their own provider or will choose to see a different provider or visit an emergency room, compromising both access and continuity. In our data, Figure 4b demonstrates this effect: The baseline (or original) resident case mixes are uneven, causing some residents to have significantly more visits than others; this results in a high visit standard deviation. Overburdened residents will have a higher chance of exceeding available capacity, leading potentially to longer wait times and losses in continuity. The greater the scale of reassignment, the less the variation in visits from one resident to another and the greater the likelihood that such panels will be able to provide acceptable levels of access and continuity in the long term.

On a practical side, patient reassignment presupposes knowledge of the composition of your panels. Unfortunately, this is not often easily achieved. Identifying who is responsible for whom is often a moving target in the fluid environment of clinical practice. For example, is a primary care physician responsible for a patient who is registered to her practice because of a change in the patient’s insurance but who has not yet been seen by the physician? Is that patient part of her panel, or is he part of the panel of the primary care physician who last treated him? Constructing a list of

### Table 2  Truncated Table Illustrating the Case-Mix as a Function of the Number of Patients Who Span $k$ Major Disease Categories for a Sample of 64 IMA Residents

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Note: IMA = Internal Medicine Associates; Res = resident. This truncated table illustrates the case-mix as function of the number of patients who span $k$ major disease categories for a sample of 64 IMA residents (the same residents shown in Table 1). The value of $k$ is used as a proxy for patient complexity; patients who span a large number of diseases are more complex. Here, for brevity, $k$ ranges from 1 to 20. For example, there are 7 patients in Resident 5’s panel whose diagnoses fall in 8 different major disease categories; in contrast, Resident 4 has only 2 such patients. Standard deviations for a particular $k$ reflect nonuniformity in patient complexity across resident panels. There standard deviations for $k = 11, 12, and 13$ are the highest, indicating that this sample of IMA residents differs significantly at those complexity levels. The complete table has been truncated for clarity. The full table is available on request. Because the table is truncated, the row count for an individual resident may be larger than currently visible.
Figure 2 Standard deviation (STD) of number of diagnoses in the major disease categories across all 64 residents at Internal Medicine Associates (IMA). The major disease categories that have the greatest standard deviation in the variation across residents are shown from left to right on the x-axis. Acute Unknown and Acute ObGyn are the major disease categories with the greatest nonuniformity in the baseline. ObGyn, obstetrics gynecology; HemOnc, hematologic/oncologic; CVS, cardiovascular; Endo, endocrine; GI, gastrointestinal; MSK, musculoskeletal; Derm, dermatologic; Unk, unknown; Psych, psychiatric; GU, genito-urinary; Imm/Rheum, immunologic/rheumatologic; Ophth, ophthalmologic; Metab, metabolic; Gen, genetic.

Figure 3 Standard deviation (STD) of number of patients who span k major disease categories across all 64 residents at Internal Medicine Associates (IMA). Standard deviation peaks from $k = 8$ to $k = 15$, suggesting that nonuniformity in resident panels is greatest at these levels of patient complexity.
patients in a panel even when patients are known in the system can be challenging.\textsuperscript{15,16} We were fortunate that the resident panels studied in this project were of limited size and were well supervised by one of the authors (B.F.). However, complete knowledge of the system is not necessary if the system is large enough or if these changes can be spread over time. In such cases, the variability in the reassignment process in an incompletely specified population itself will be smoothed out the larger the population or the longer the period of time. This latter situation is more reflective of health care systems in which probabilistic allocation based on practice case-mix, panel size, and patient characteristics is likely more desirable because of the cost/benefit of acquiring and managing population-level data.

As we go forward, we will test this algorithm in the real world with the local resident training program. We also plan to quantify satisfaction measures for patients, residents, preceptors, and administrators as well as clinical outcomes for patients. We will continue to develop better and simpler ways with which to compare panels across systems. This will allow us to better understand our health care system and the effect of such interventions on it. These measures will need to be, in part, population health measures (e.g., vaccination rates), system measures (e.g., wait time, continuity), and patient preference (e.g., decision-making styles, geography, culture).

Other day-to-day operational aspects need to be considered in future work. Residents are essentially fixed to the clinic where they are assigned. However, because residents work part time, matching a patient’s availability with the resident’s availability may not always be possible. This was not perceived as a regular problem in the clinic considered. Continuity is generally more vital for prescheduled requests, which involve routine checkups or follow-up and monitoring of chronic conditions. Because such requests are scheduled in advance, a patient-resident on a desired day is more feasible. An urgent request requiring speedy access may be directed to a different resident (if she has any capacity available that day), but it may be better for this secondary resident to share the same preceptor as the original resident; the presence of the preceptor can help retain some measure of continuity.

From a methodology perspective, the reallocation problem we are addressing is the deterministic resource allocation problem where \( n \) tasks or jobs (in our case patients) have to be assigned to \( m \) resources (in our case residents). The general framework resembles some classic scheduling and optimization problems. A mixed-integer programming (MIP) formulation would have been the truly optimal way to address the problem. However, this would possibly involve a binary decision variable to indicate whether patient \( i \) should be in resident \( j \)’s panel. When the number of patients is large, obtaining a solution of the mixed integer program may take a significant amount of computation time.

Our reassignment algorithms are equivalent to the largest task being assigned to the resource with the lowest total current workload. This is a commonly used heuristic for the resource allocation problem to minimize workload differences. It is known to produce close to optimal solutions. The worst-case performance of this heuristic is \((4/3 - 1/3m)^9\), where
$m$ is the number of resources (residents). When $m = 2$, the longest process time (LPT) in the very worst case is $7/6$ of the optimal value; when $m = 3$, the worst case is $10/9$ of the optimal value. Furthermore, the algorithm runs very quickly, can be implemented easily with Excel macros, and can be customized by the practice more easily than a mixed integer program.

In conclusion, a systematic approach to how we organize our practices, panels, and health delivery systems can help quantify the associated benefits and tradeoffs and set the stage for more informed redesign.

REFERENCES