Optimal Panel Redesign

Title: Optimizing outpatient residency training: A method for balancing clinical experience with access to care

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Abstract (328 words)

**Background:** To receive adequate training experience, resident panels in teaching clinics must have sufficiently diverse patient case-mix. However, case-mix differs from one resident panel to another, resulting in inconsistent training, and uneven levels of access and continuity for patients. The beginning of the academic year, when one third of the residents graduate, provides an opportunity for residency clinics to address these imbalances by reassigning patients.

**Method:** Encounter data from primary care residency clinics at Massachusetts General Hospital from 7/2008 - 5/2010 (64 residents and ~3,800 patients) was 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 calculating the standard deviation for each disease category, patient panel size, and annual visit frequency. To balance case-mix in resident panels, patient reassignment algorithms (to be applied at the start of the academic year) 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 three scenarios: 1) within preceptor, 2) within a group of preceptors, 3) across entire practice. The results were compared with baseline case-mix (pre-July 2012) and post-July case-mix.

**Results:** All three reassignment algorithms produced significant reductions in standard deviation of either number of disease categories or diagnoses across residents, when compared to baseline (pre-July 2012) and actual July 2012 reassignment. Reassignment across a group and clinic
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provided the second best and best results but both come at the cost of reduced patient-preceptor continuity.

**Conclusion:** Systematically reallocating patient panels annually in teaching clinics potentially can improve the consistency and breadth of the educational experience. Since panel case-mix also impacts visit rates and thereby access and continuity, these measures are also balanced. The method in principle can be extended to any healthcare system reform where there is either patient or clinician turnover.
1. Introduction

Teaching clinics must satisfy at least two critical but often conflicting demands. They must provide a quality teaching experience while at the same time provide patients timely access to care[1-4]. Quality training requires residents to have consistent exposure to a range of clinical experiences from which to learn along with easy access to their preceptors. Timely access for patients means among other things seeking to minimize patient wait time and maximizing continuity between patient and practitioner. Continuity allows the patient and clinicians to gain experience and trust with each other and potentially improve health outcomes [5-7]. The distribution of types of patients (age, gender, etc.), the range and frequency of clinical problems within these patients[8], the number of patients with specific types of problems/learning opportunities and the absolute number of patients a resident is responsible for (panel size) directly influences both range of experiences available during training and access to care for patients[9, 10].

During their 3-year training, each resident manages a panel of patients. Each resident also works with one preceptor for the 3-year duration; the resident-preceptor link is typically maintained throughout. A preceptor has 3-4 residents and a preceptor typically does not share residents with other preceptors. Patients in the resident panels also belong to the preceptor’s panel; preceptor panels therefore are larger. When a patient from the panel visits the clinic, she may see both the resident and 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 to maintaining continuity.
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Every year, 1/3 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 in case-mix, resulting in an inconsistent training experience. Residents with more complex patients are also likely to have higher visit rates than available capacity, adversely affecting timely access to care (wait time for appointments) and patient-clinician continuity [16].

We set out to develop a framework for systematically optimizing patient reassignment on an annual basis (at the beginning of the each academic year), so as to: balance the range of clinical experiences resident are exposed to during their training, and thereby also balance patient access to and continuity with their clinicians. We designed a computer algorithm that sorts patient panels by weighting factor(s) of interest, for example, age, gender, 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. In this paper we discuss the framework and the projected results of this process for a primary care internal medicine residency clinic at Massachusetts General Hospital.

2. Methods

2.1 Data description

We collected encounter data from primary care residency clinics affiliated with Massachusetts General Hospital over a twenty-one month period (July 1, 2008 to April 30, 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 ten-year increments. These classifications were chosen as preliminary parameters to determine frequency demographics and the dependency patient visits may have with regards to age and gender. The largest resident clinic in this sample with 64 residents was chosen to be examined pre- and post-real world reassignment as it had the most real world reallocation opportunities within, resident, preceptor and pod (preceptor group).

2.2 Measures of Panel Case-Mix and Complexity

We use two 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 diagnoses 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, etc. In all there were 44 disease categories.

*Diagnoses Span*

Individual patients may contribute more than one diagnosis to a patient panel and that a single patient’s set of diagnoses may fall across several *different* disease categories. For example, one patient may have 5 diagnoses but all be 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.

**2.3 Standard Deviation as a Measure of Imbalance**

The imbalance or non-uniformity across residents was quantified by using standard deviation (SD) measures. For example, if there are four 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 four numbers, 51.46 (standard deviation for diagnoses = SD_DIAG). The higher the SD_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.

**2.3 Patient Reassignment Algorithms**

Our algorithms can be broadly classified into ones using diagnosis count and ones using diagnostic category span.

The algorithm is executed in two 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 one at a time, to the panel with the smallest count of diagnoses, i.e., the next most complex patient on the list is assigned to the resident who has the smallest count of number of diagnoses. In case of a tie, patients are allocated according to the next highest priority criteria such as panel size. In the case of a tie across all criteria patient are randomly assigned between equivalent panels.

The algorithms are applied to three different settings:

1) Restricted Reassignment: 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 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 that are not graduating. No patients are reassigned across preceptors and patients maintain continuity with the preceptor.

3) Reassignment Within Group (RWG): Patients are reassigned for all residents within a group of preceptors. The motivation behind RWG is 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.

2.4 Predicting re-allocation performance

We then tested the potential effect of these four algorithms 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, pre (Original/Baseline) and post the July resident turnover (Actual). Our method, however, is applicable to any number of residents and for any number of patients.

3. Results

Patient demographics and visit variation is 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 SD within category is 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 non-uniformity -- 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 that span \( k \) major disease categories for the same residents in Table 1. The value of \( k \) is used a proxy for patient complexity; 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 constrast, Resident 4 has only 2 such patients. Standard deviations for a particular $k$ reflect non-uniformity in patient complexity across resident panels. There standard deviations for $k = 11, 12$ and $13$ 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 reassignment within preceptor, group and clinic have lower standard deviations compared to the baseline (original, pre July 2012) and actual (July 2012 reassignment) as well as the restricted reassignment.

Figure 3 shows the standard deviation of number of patients that span $k$ major disease categories across all 64 residents. Standard deviation peaks from $k = 8$ to $k = 15$ suggesting non-uniformity in resident panels is greatest at these levels of patient complexity. As in Figure 2, reassignment within preceptor, group and clinic 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 reassignment across clinic reduces to near zero the variation in both panel sizes and visits.

4. Discussion

Systematically reorganizing patient panels can substantially improve the range of educational experiences for trainees over the current state of affairs and potential improve time to access for patients as well. An algorithmic approach works best when patients are most free to move between providers. For example, if everyone was free to be reassigned, time to access could be
reduced to its potential minimum and educational exposure to its maximum. However, this degree of reassignment is usually not possible, 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 and minimizes loss of continuity and is likely more acceptable. This is particularly relevant since this result is consistent with the current movement towards group practices and medical homes[11-13]. In addition, reassigning within groups has the added advantage of preserving matching on unobserved variables that may have been driving selection for the 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 two or more incoming residents, and perhaps more than one preceptor may be involved in the discussion. Such handovers need to be planned in advance and adequate time needs to be budgeted into 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 interesting direction for future work is 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.

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 PCP responsible for a patient registered to her practice because of a change in the patient’s insurance but who has not yet seen by the clinician? Is that patient part of her panel or is he part of the panel of the PCP who he was last seen by? Constructing a list of patients in a panel even when patients are known in the system can be challenging[14, 15]. We were fortunate that the resident panels studied in this project were of limited size and well supervised (BF). However, it should be noted that complete knowledge of the system is not necessary if the system 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 smooth out the larger the population or the longer the period of time. This latter situation is more reflective of healthcare systems where 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 be testing 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 also need to
continue to develop better and simpler ways with which to compare panels across systems. This would allow us to better understand our healthcare system and the effect such interventions on them. These measures will need to be in part population health measures (e.g., vaccination rates), part system measures (e.g., wait time, continuity) and part patient preference (e.g., decision making styles, geography, cultural).

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

Tables

**Table 1.** Case-mix for 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 of diagnoses counts under each category is also 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 non-uniformity -- and thereby inconsistency in resident training -- across residents for a particular disease category.

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### Optimal Panel Redesign

Complete table truncated for clarity. The full table is available at request.
Table 2. Case-mix as function of the number of patients that 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 non-uniformity 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.

| Res | Case Span | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | *** |
|-----|-----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 1   | 0         | 0 | 0 | 0 | 4 | 1 | 3 | 5 | 1 | 4 | 5 | 8 | 3 | 7 | 1 | 5 | 3 | 4 | 4 | 3   | *** |
| 2   | 0         | 1 | 2 | 5 | 4 | 5 | 2 | 5 | 2 | 4 | 4 | 3 | 3 | 3 | 6 | 0 | 3 | 1 | 5 | 0   | *** |
| 3   | 0         | 1 | 0 | 0 | 2 | 1 | 1 | 3 | 4 | 5 | 6 | 3 | 2 | 2 | 1 | 0 | 6 | 2 | 0 | 1   | *** |
| 4   | 0         | 0 | 1 | 3 | 2 | 3 | 3 | 2 | 2 | 3 | 3 | 3 | 6 | 0 | 0 | 0 | 2 | 5 | 1 | 1   | *** |
| 5   | 2         | 1 | 1 | 3 | 1 | 7 | 5 | 7 | 3 | 2 | 3 | 4 | 3 | 1 | 2 | 1 | 2 | 3 | 1 | 1   | *** |
Complete table has been truncated for clarity. The full table is available at request.

*N.b., Because table is truncated row count for an individual resident may be larger than currently visible*
Figures

Figure 1. Demographics and visits by age and gender
**Figure 2.** Standard deviation of number of diagnoses in the major disease categories across all 64 IMA residents. 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 great non-uniformity in the baseline.
**Figure 3.** Standard deviation of number of patients that span $k$ major disease categories across all 64 IMA residents. Standard deviation peaks from $k = 8$ to $k = 15$ suggesting non-uniformity in resident panels is greatest at these levels of patient complexity.
Figure 4. Standard deviations in number of patients (panel size) and yearly visits (STD_PAT and STD_VIS) across all 64 IMA Residents by Original (Baseline) and all reassignment methods. The average panel size per resident was 59. The average expected yearly visit is 537 per resident.