

Reducing emergency admissions: are we on the right track?

Most attempts to reduce emergency hospital admissions are focused on people at high risk. **Martin Roland** and **Gary Abel** highlight the misconceptions behind this approach and suggest what to do about them

Emergency admissions are a popular target in the drive to improve quality of care and save money. In the NHS rates of admission from primary care practices are under increasing scrutiny because it is widely believed that many admissions could be avoided by better primary care. However, evidence about what is effective is lacking, and misconceptions may lead to naïve or unrealistic expectations of what can be achieved.

Problem of rising admissions

Emergency or unscheduled admissions have been rising for several years (fig 1), with emergency admissions commoner among elderly people and those with comorbidities.^{1 2} In part the rise results from changes in the health service that may have nothing to do with patients' health. For example, introduction of a target in 2004 that patients should wait no longer than four hours in emergency departments has been seen as a cause of increased short stay emergency admissions.³ In addition, hospitals had incentives to improve data collection systems after emergency admissions were included in their payment schedules in 2006-07.⁴

Nevertheless, some of the increase seems to be real, and improving primary care could prevent a significant number of people being admitted as emergencies. It has been estimated that around £2.3bn (€2.9bn; \$3.7bn) could be saved by reducing admissions among "frequent fliers"—patients with multiple hospital admissions, who are believed to use a disproportionate share of



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resources.⁵ Most interventions involve identifying patients at risk of admission and providing a case manager—for example, a community matron—to support them. But there are some fundamental flaws in this approach, as we describe below.

Overestimating the importance of frequent fliers

Much effort has been devoted to find algorithms that can identify patients at high risk of

hospital admission. In the UK, models such as the patients at risk of rehospitalisation (PARR) model, PARR++ model, and the combined model have added increasing sophistication to the identification of patients at risk of admission.^{6 7} In the US there is currently a \$3m prize on offer for the group that can produce the best algorithm to predict future use of hospital bed days.⁸

Table 1 | Percentage reduction in admissions in each risk group alone required to meet overall targets for reductions in emergency admissions

Target overall reduction (%):	% reduction required in risk group			
	Very high risk (0.5% of population)	High risk (0.5-5% of population)	Moderate risk (6-20% of population)	Low risk (80% of population)
1	10.8	4.0	3.9	2.5
2	21.5	8.1	7.8	5.0
3	32.3	12.1	11.8	7.5
4	43.0	16.2	15.7	10.0
5	53.8	20.2	19.6	12.5
10	107.5	40.4	39.2	25.0

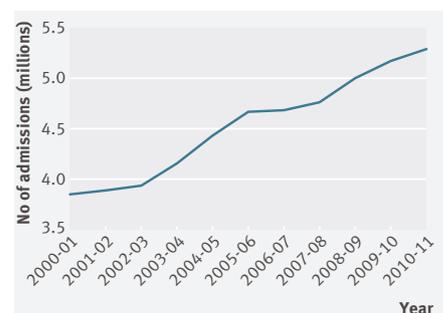


Fig 1 Emergency admissions to NHS hospitals in England, 2000-11²

These models are based on an assumption that interventions should focus on people at greatest risk of hospital admission (fig 2). The epidemiologist Geoffrey Rose pointed out a potential pitfall in this argument in relation to hypertension over 20 years ago: high risk patients don't actually account for most admissions—most admissions come from low risk patients, and the greatest effect on admissions will be made by reducing risk factors in the whole population rather than in a small group of high risk people.¹⁰ This is further illustrated in table 1, which shows the size of effect needed to reduce overall admissions by different target percentages by intervening in different risk groups.

Table 1 shows that in order to reduce emergency admissions by 10% by concentrating just on the 0.5% at highest risk of admission, more than the total number of admissions in this group would need to be avoided (107.5%). If the next group down were the focus of an intervention (the 4.5% of the population at high risk), 40% of their admissions would need to be avoided to produce an overall 10% reduction in admissions, which is still an improbably large figure. And even with the high risk group, the numbers start to cause a problem for any form of case management intervention—5% of an average general practitioner's list is 85 patients. To manage this caseload would require 1 to 1.5 case managers per GP.¹¹ This would be a huge investment of NHS resources in an intervention for which there is no strong evidence that it reduces emergency admissions.^{12 13}

An alternative approach is to target the intervention on a much larger group—for example, a current integrated care pilot plans to target a range of interventions on nearly half of elderly people in two London districts.¹⁴ However, the cost effectiveness of such broadly based population approaches has yet to be established.

Ignoring regression to the mean

A common approach in evaluating interventions to reduce admissions is to identify people at risk on the basis of multiple past admissions, deliver some form of intervention, and then examine whether the admissions in the original cohort go down. The problem is that admissions in this group go down without any intervention, a phenomenon known to statisticians as regression to the mean. The consequence of regression to the mean is that patients with a history of multiple admissions will, on average, have fewer admissions in future than they had in the past. So, for example, when we followed admission patterns for five years after a year in which a cohort of older people had been admitted twice or more as emergencies, we found that within two years they had the same pattern of admissions as the rest of

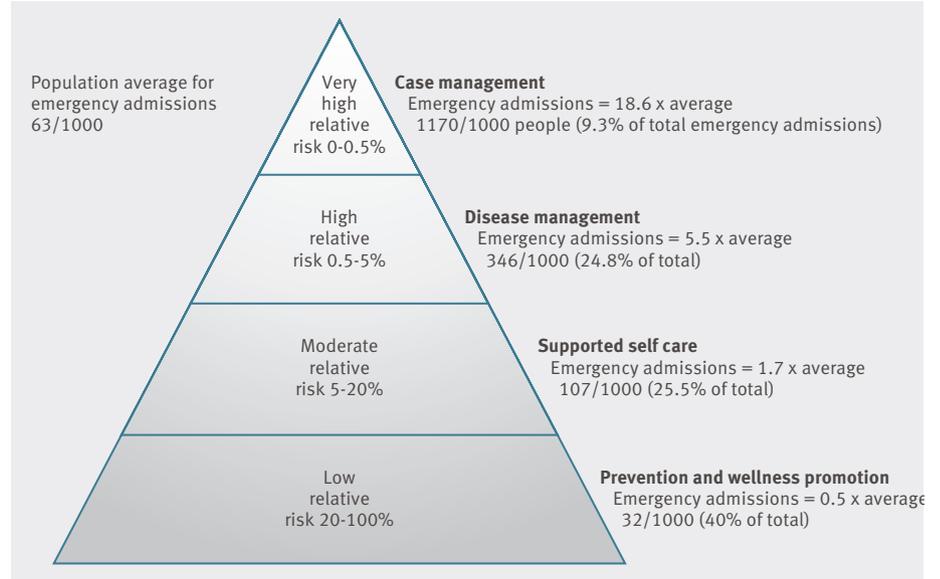


Fig 2 | Rates of emergency hospital admission by different risk patients (based on Wennberg et al 1996).⁹ Percentage of all emergency admissions is equal to the relative rate multiplied by the population group

the population of their age.¹⁵ Ignoring regression to the mean is a great way of showing that your intervention “works.” The way round this is either to find a comparison or control group of patients with no intervention, or to look at changes in patterns of overall use—for example, is your intervention associated with an overall reduction in admissions for over 75s (more likely to be a true effect) or just a reduction in admissions among those who received an intervention (more likely to be regression to the mean)?

Ignoring the possibility of supply induced demand

Even when studies allow for regression to the mean, interventions to reduce admissions often show little effect. We illustrate this with the example of intensive case management, which is a common model chosen for reducing admissions among frail elderly people. The first large scale implementation of case management in England was the Evercare scheme. A case-control comparison of emergency admissions from 62 general practices in which the intervention took place and 7695 control practices suggested an increase in emergency admissions, though it was not statistically significant.¹² More recently, a case controlled evaluation of 3646 patients receiving case management interventions in the English integrated care pilots and 17 311 risk matched controls found a significant increase in emergency admissions.¹³ In both cases, the increase occurred despite anecdotal evidence that admissions had been avoided.

The only way in which these findings are compatible is that, as well as reducing admissions, case management resulted in some additional

admissions that would not otherwise have taken place. It's not hard to see why this might occur. Economists are more familiar than politicians and healthcare managers with supply induced demand, which simply means that when you put more services in, staff find more problems and more people needing care. NHS Direct, a 24 hour medical phone advice line in England, is a classic example of an additional service that was designed to reduce the use of emergency services but instead provided an additional (and popular) facility.¹⁶ Supply induced demand is one reason why interventions designed to improve quality and coordination of care are much more likely to show improvements in quality than reductions in cost.^{17 18}

Assuming that all interventions are beneficial

As well as ignoring the possibility that some interventions may have the opposite effect to that intended, it is also unwise to assume that all interventions are without risk of harm. For example, two recently published high quality randomised controlled trials of interventions designed to keep people out of hospital showed increased deaths among the intervention groups: a trial of self management in chronic obstructive pulmonary disease was terminated prematurely because of increased mortality in the intervention group,¹⁹ and a trial of telemonitoring found an unexpected increase in mortality in the intervention group.²⁰ We are not arguing that these interventions are necessarily harmful, simply that like drugs, healthcare interventions have the potential for unintended consequences. Too often, interventions are introduced without sufficient critical attention to the possibility of unin-

tended consequences. It is possible that there would be unforeseen negative consequences for patients if GPs were under excessive pressure to reduce admissions.

Forgetting that substantial amounts of variation can be due to chance

The pressure to reduce healthcare costs is great, and general practices in England are now given regular feedback on their numbers of specialist referrals and hospital admissions. Often these figures are based on very small numbers (such as a practice’s referrals to one specialty over six months). This can highlight variation that is simply due to chance, as even large variations can be explained by chance when the average number of events is small. Table 2 gives a guide to the amount of variation that might be expected due to chance alone. For example, if a practice would be expected to have 25 admissions in a given time, that figure could vary from 22 to 28 for 50% of the time just due to chance. Variation of the amounts illustrated in the 50% column in table 2² should not be highlighted. To be more confident that variation is not due to chance a wider range should be used.

Thinking that we know what to do

One of the problems in reducing emergency admissions is that we don’t know what to do. Apart from a few exceptions, such as congestive heart failure, evaluations of interventions to reduce emergency admissions have been disappointing.²¹ This is partly because policy makers and health service managers are reluctant to submit changes in service delivery to rigorous evaluation, such as randomised controlled trials. This can lead to ambiguous or inconclusive findings. However, we also don’t have a sufficiently clear understanding of the problems that lie behind the rise in emergency admissions or any coherent theory to develop interventions that are likely to be successful. For example, much energy has concentrated on avoiding admissions by providing better primary care with little consideration of the role of secondary care—for example, the

lack of any incentive for specialists to engage with primary care physicians to develop systems where primary and secondary care are effectively integrated to achieve a common set of goals.

A more considered approach

So what should clinicians and health service managers do? It is easier to see the problems than the solutions to emergency admissions. We do, however, suggest some guidelines for those needing to focus on this important and expensive aspect of healthcare:

Don’t assume that reductions in admissions in a high risk group are due to your intervention—

Evaluate your intervention against changes in overall patterns of admission or using a control group

Don’t assume there is a correct level of admission or referral to hospital— Clinical audit makes numbers meaningful and should be used to identify where there are problems in care

Don’t assume that fewer admissions or referrals are necessarily better— Doctors with low rates of specialist use may be a danger to their patients, just as high referrers may be wasting resources. Use clinical audit to bring meaning to crude rates of referral or admission

Be cautious about using data for short time periods or referrals to single specialties—

Random fluctuations may account for much of the apparent variation in provider performance when numbers are small. Use table 2² to assess how much variation might be due to chance

Choose interventions that are evidence based— Use information from reliable sources such as the Cochrane Effective Practice Group (<http://epoc.cochrane.org>), the King’s Fund,²² or systematic reviews.²¹

However, bear in mind that context is important. Carefully shaping the way an intervention is introduced may increase its effectiveness, and don’t forget that most changes can have unexpected consequences too.

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Table 2 | Variation in number of referrals or admissions that would occur if variation was due solely to chance (assuming a Poisson distribution)

Expected No of events	Expected range. % of time that results would fall outside range by chance alone:		
	50%	10%	5%
5	3-6	2-9	1-9
10	8-12	5-15	4-16
25	22-28	17-33	16-35
50	45-54	38-61	37-64
100	93-106	84-116	81-120
200	190-209	177-223	173-228
500	485-515	463-536	457-544
1000	979-1021	948-1052	939-1062