Conrane IHS
International Health Solutions

6. Applied Intelligence

Informatics, Care Coordination and Resource

Equity

- Introduction to Integrated Risk Intelligence System iRIS
- Population risk profiling and case mix adjustment
- Supporting long term conditions management
- Predictive modelling and its advantages
- Supporting the Care Coordination pathway
- Securing equitable resource allocation
- Risk adjustment in Primary Care budgeting

Conrane-IHS
International Health Solutions

Best practice in integrated care

iRIS Integrated risk intelligence system

iRIS© is our bespoke platform for ACGs© with reporting designed for clinicians by clinicians

iRIS© can incorporate social care data for holisitic care management and integrated care commissioning

iRIS© underpins equitable resourcing for CCGs commissioning primary care

iRIS© supports the entire care coordination pathway

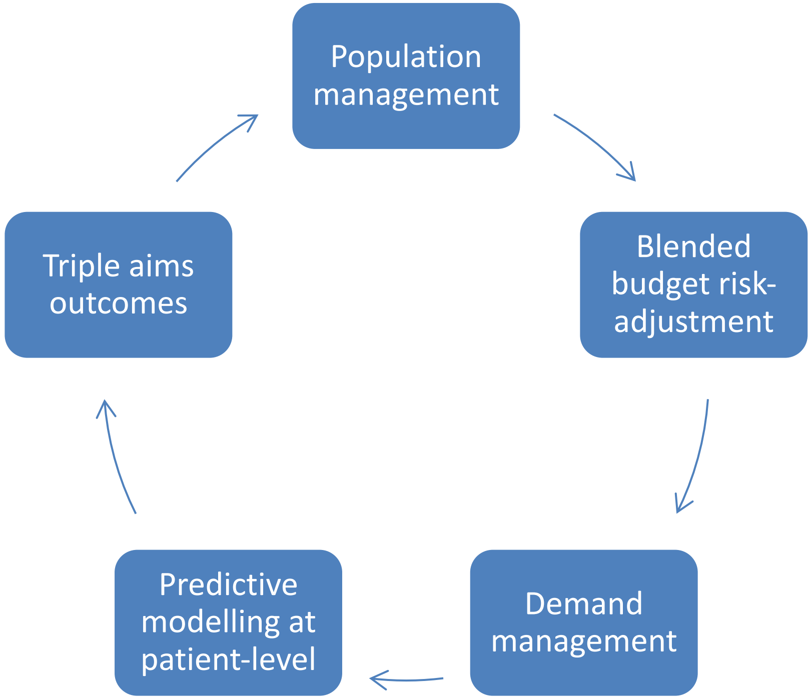
iRIS© training designed by our expert case managers who deliver it at GP practice level

iRIS© informs planning and commissioning of health and social services but also the proactive management of individuals to promote and prolong independence

iRIS© supports CCGs with the challenges of continuing health care identifying patients at risk of nursing home services, and identifying the associated financial risk

iRIS - Integrated Risk Intelligence System

Applying tools such as the Johns Hopkins Adjusted Clinical Groups (ACG)® System



What are the role and value of risk stratification in health and social care development? At Conrane we hold that it is much more than just identifying patients for case management, virtual ward or other intervention for patients with complex needs.

The range of data required and the effort involved in applying this down to individual patient level requires that we employ it to add maximum value to patients and their local health and social care communities.

No risk stratification available to the NHS or worldwide is better able to deliver this than the ACG system.

Section 1 – Application

In the current UK market, the NHS faces a confusing choice of several risk stratification tools.

There are none more comprehensive in functions than the Johns Hopkins ACG Suite. With our specialist team at Conrane we bring nearly two decades of projects in risk assessment, successful care coordination, and equitable resource allocation.

This guide explains this functionality and provides examples drawn from actual current ACG deployments by our consultants.

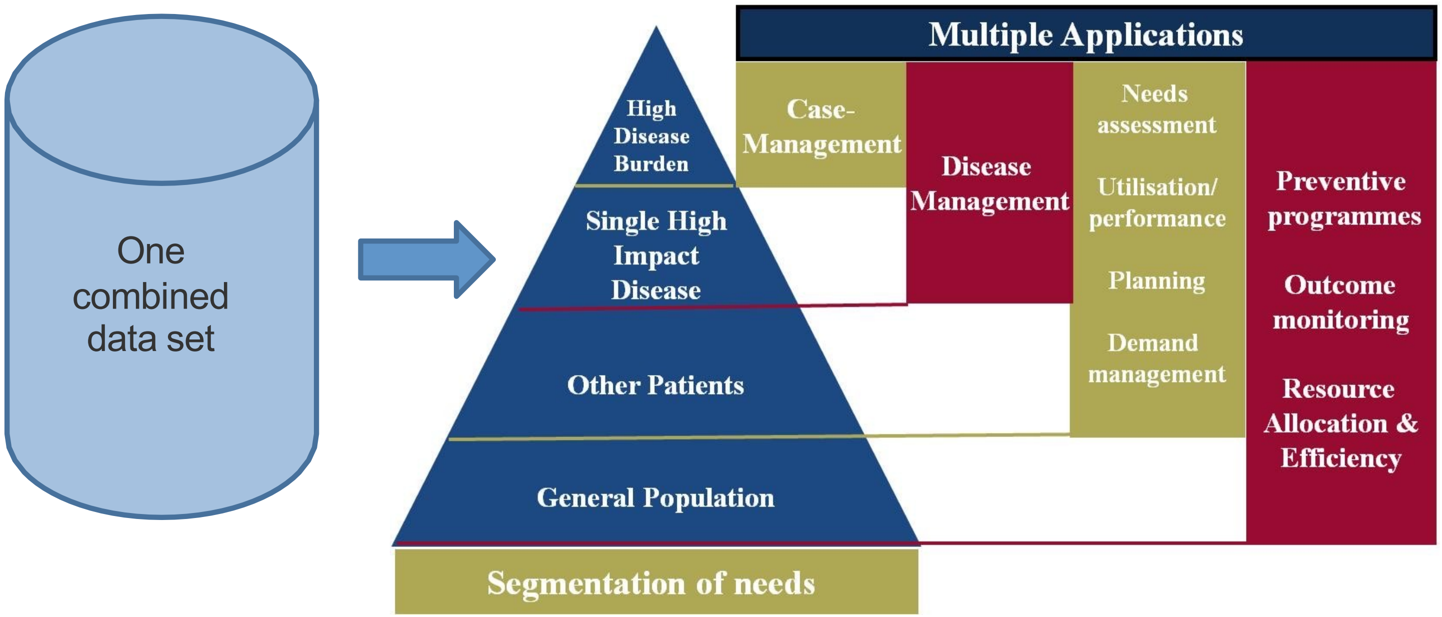
- Introduction and Overview
- Three main functions
- A combined flexible data set
- Incorporating social care data
- Mapping and dashboards
- Section 2 – Long Term Conditions
- Section 3 – Case-mix and resource management
- Section 4 – Our Development Team

Overview of Adjusted Clinical Groups AACGs

Gathering data for a risk stratification tool can be a resource and time intensive process.

The ACGs return in benefits matches this time investment.

One combined data set delivers multiple applications to today's health and social care business intelligence.



Functions of the ACG Risk Stratification System

There are three core functions of the ACG system which reflect the development of the tool in response to user feed-back.

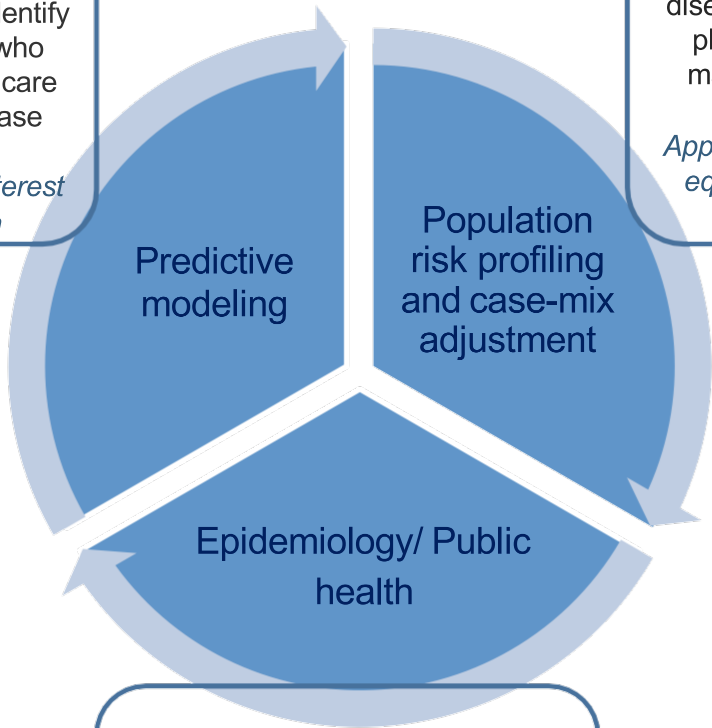
First, it started as a population case-mix adjustment tool to link resources to need and support equitable allocation.

Second, a leading-edge predictive model was then added to the ACG suite.

Third a series of epidemiological or public health functions were added.

The *prospective* application of risk adjustment measures and statistical forecasting to identify high needs individuals who would likely benefit from care coordinated including case management
Application of primary interest to care coordination

The health status of a population and burden of disease are measured to inform planning services, resource management and assessing outcomes.
Application of primary interest to equitable resource allocation and monitoring



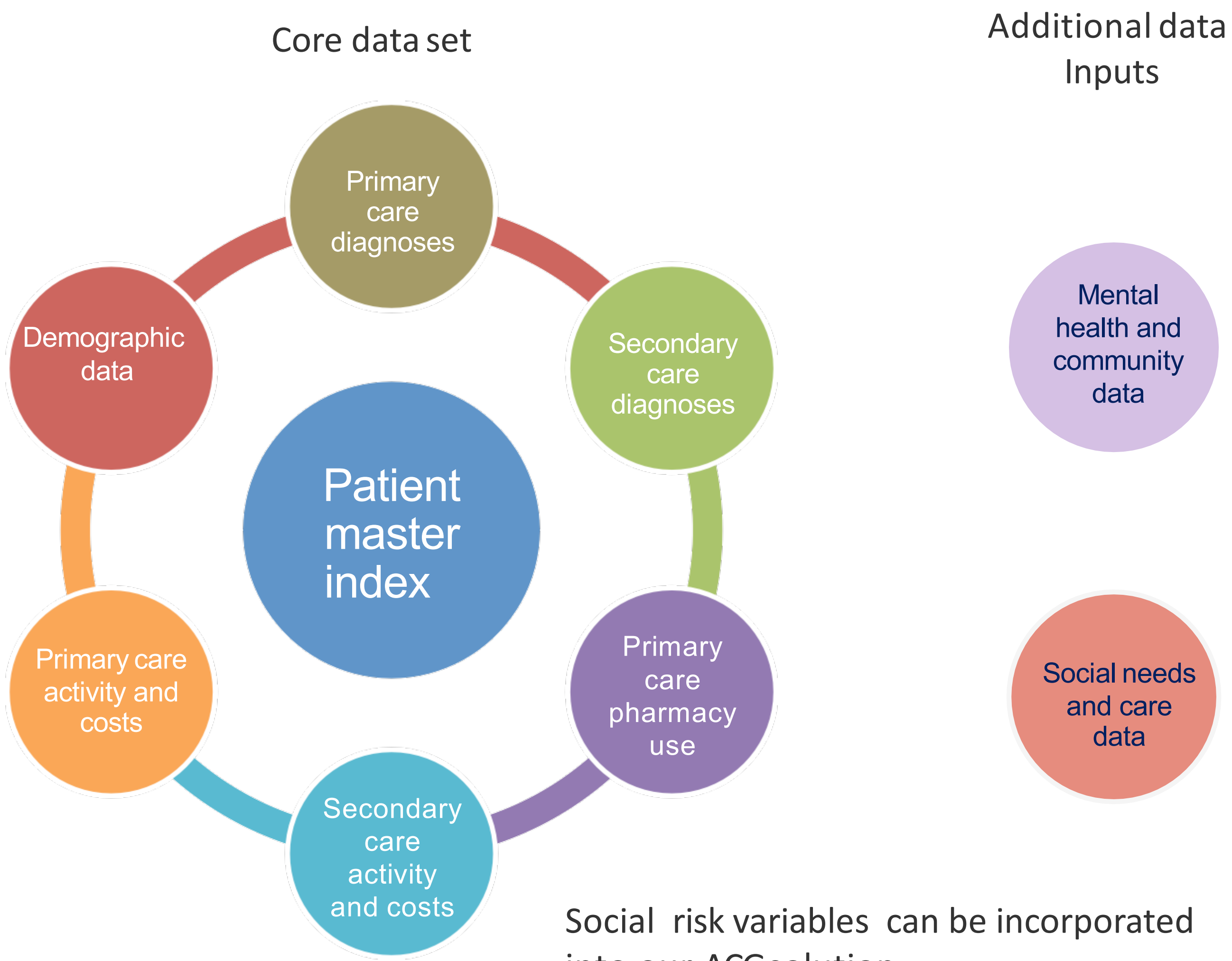
Describes and quantifies patterns of disease including standardised prevalence rates and morbidity ratios based on local diagnostic data-
Application supports prevention strategies and other public health activities

1.4. A combined, flexible data set

The core minimum data set for ACGs includes diagnoses, pharmacy use (by type of drug) and costs. Costs are derived by adding tariffs and unit costs to activity. The data set is derived for each patient.

The flexibility of ACGs allows other data to be inputted such data from mental health and community. Providers.

Data on social needs and costs can also be incorporated



Social risk variables can be incorporated into our ACG solution

1.5. ACGs and social care data

We are now working with our academic partners to create an *integrated risk stratification* approach.

Our ACG integrated care solution can incorporate social care risk factors which predict both high health care costs and social care costs.

Our solution is practical and deliverable.

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Our ACG integrated care solution can incorporate social care risk factors which are predictive of both high health care costs and social care costs. This will include

- Social needs factors listed alongside all current ACG risk markers support patient prioritization and care planning for holistic care coordination;
- Developmentally, we will be working with our partners to integrate social need variables into the predictive modeling process as a innovation for predicting health and social care needs.

The benefits include:

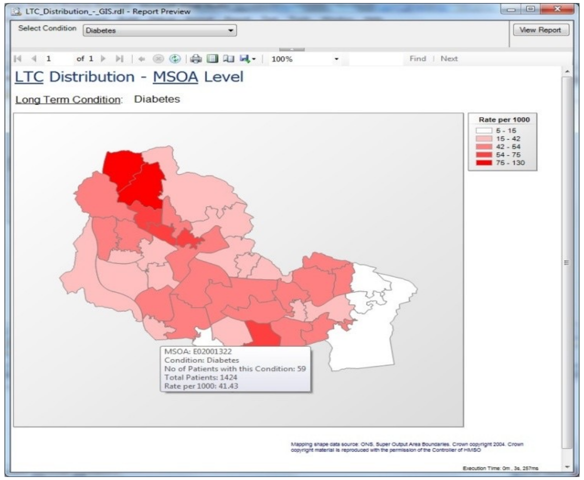
- A truly integrated care data base for individuals and specific patient groups;
- A wholeAsystem (health and social care) costing for each individual patient and thus for GP practices, localities or any geographic subAset;
- Allows the monitoring of any cost transfers between health and social care arising from specific patient management programmes.

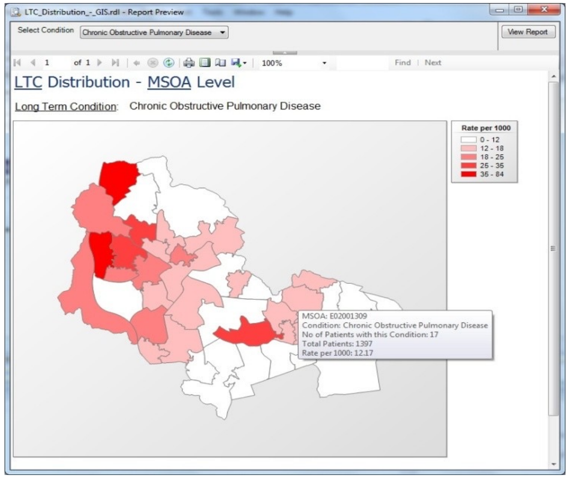
ACGs– interactive mapping and dashboards

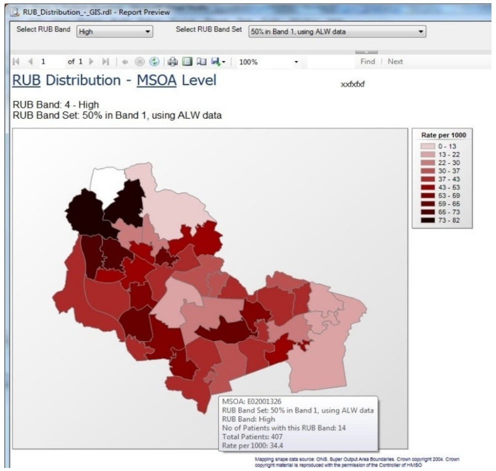
Within the IHSSSRS version of ACGs we are able to link data to mapping and dashboard soiware.

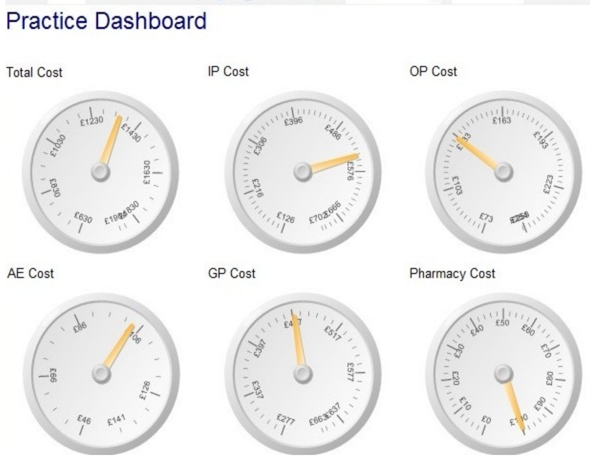
The maps are structured using super output areas so as to be of interest to public health. Both these graphical data presentations are interactive. Hence by clicking on a segment of the map, a list of these patients is generated.

Patient identifiable data is only available to those users with access rights (as locally determined).









Section 2 – Long-term Conditions

Risk stratification tools that only highlight relative risk can be of limited value to clinical staff.

The IIRSACG solution supports the entire care coordination patient pathway.

We also offer training lead by expert case managers in order to embed the data into practice

- 2.1 Overview
- 2.2 Advantages
- 2.3 Predictive power
- 2.4 ACGs and ‘House of Care’
- 2.5 Clinical user feedback
- 2.6 Meeting user requirements
- 2.7 Supporting the care coordination pathway
- 2.8 Metrics, impact monitoring, and reflective practice
- 2.9 People of moderate risk
- 2.10 User access rights

2.1 Overview

The core minimum data set for ACGs includes diagnoses, pharmacy use (by type of drug) and costs. Costs are derived by adding tariffs and unit costs to activity. The data set is derived for each patient.

The flexibility of ACGs allows other data to be inputted such data from mental health and community.

Providers.

Data on social needs and costs can also be used provided it is available in standard format by NHS patient identifier

Clinical Care coordination

Predictive high risk

Patient prioritisation

Long-term conditions by risk and cost

Relative risk and progression

Co-morbidities

2.2. The advantages of the ACG predictive model

When considering risk stratification and predictive models, the first question to consider is what are we looking to achieve by implementing risk stratification and predictive modeling?

Corollary questions might be, what are we trying to predict? what outcomes are we looking to achieve? How can we best support the care coordination pathway and what is the role of practitioners in the process?

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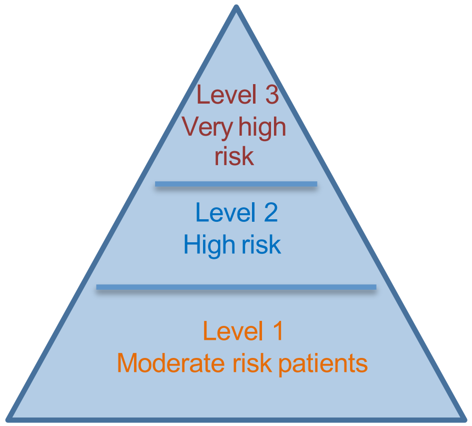
ACGs delivers the following key features of risk stratification and predictive modeling solutions:

- **Predictive power** ‐ Predictive power is measured as C‐statistic (relative reliability of the forecast), where a value of 0.5 would be equivalent to chance, and 1 would be absolute certainty. The ACG System is up‐dated regularly by researchers at Johns Hopkins University o i e n in response to user‐feedback as well as developments in the quest to improve positive predictive value. The current version of ACGs achieves a 'C' of 0.835.
- **All risk groups identified** ‐ A locality model of care coordination requires intelligence of level 3 ‐very‐high risk patients, level 2 ‐high risk patients and level 1‐ other patients with long‐term conditions who are at moderate risk. ACGs allows users to rank patients by risk and sort by diagnosis.
- **Ease of use** – Too many of these models fall into disuse because of the time required for busy clinicians to s i i through long lists which provide no relevant information other than a relative risk score. ACGs has a relative
    - **Clinical relevance** ‐ In our experience, clinicians need to be involved in patient selection and prioritisation.
    - **Supports the care coordination pathway** in addition to simply assessing risk

Risk pyramid for patients with LTCs



2.3. A predictive model of leadingAedge power

Clinical users require a tool with a low rate of 'false positive'.

The ACG System is upAdated regularly by researchers at Johns Hopkins University oien in response to this userAfeedback to improve positive predictive value.

The ACG predictive model is amongst the most powerful available to the world's healthcare systems.

"Predictions are hard, especially about the future."

Niels Bohr
Nobel Prize Winner in Physics

The ACG System draws on diagnostic, prescribing and utilisation data from primary and secondary care. From this combined database, several risk measures can be derived – both current and predictive. These begin with the individual patient and can be aggregated to each GP list, to practiceAlevel, to localities and to Clinical Commissioning Groups (CCGs).

The ACG suite includes one of the worlds most powerful predictive modelling tools.

ACGs technical specification at top 5% of risk

C:Statistic or relative reliability of the forecast *is 0.835 (where 0.5:chance and 1 – certainty)*

20% of true positives cannot be identified by any other method (e.g. prior cost and utilisation)

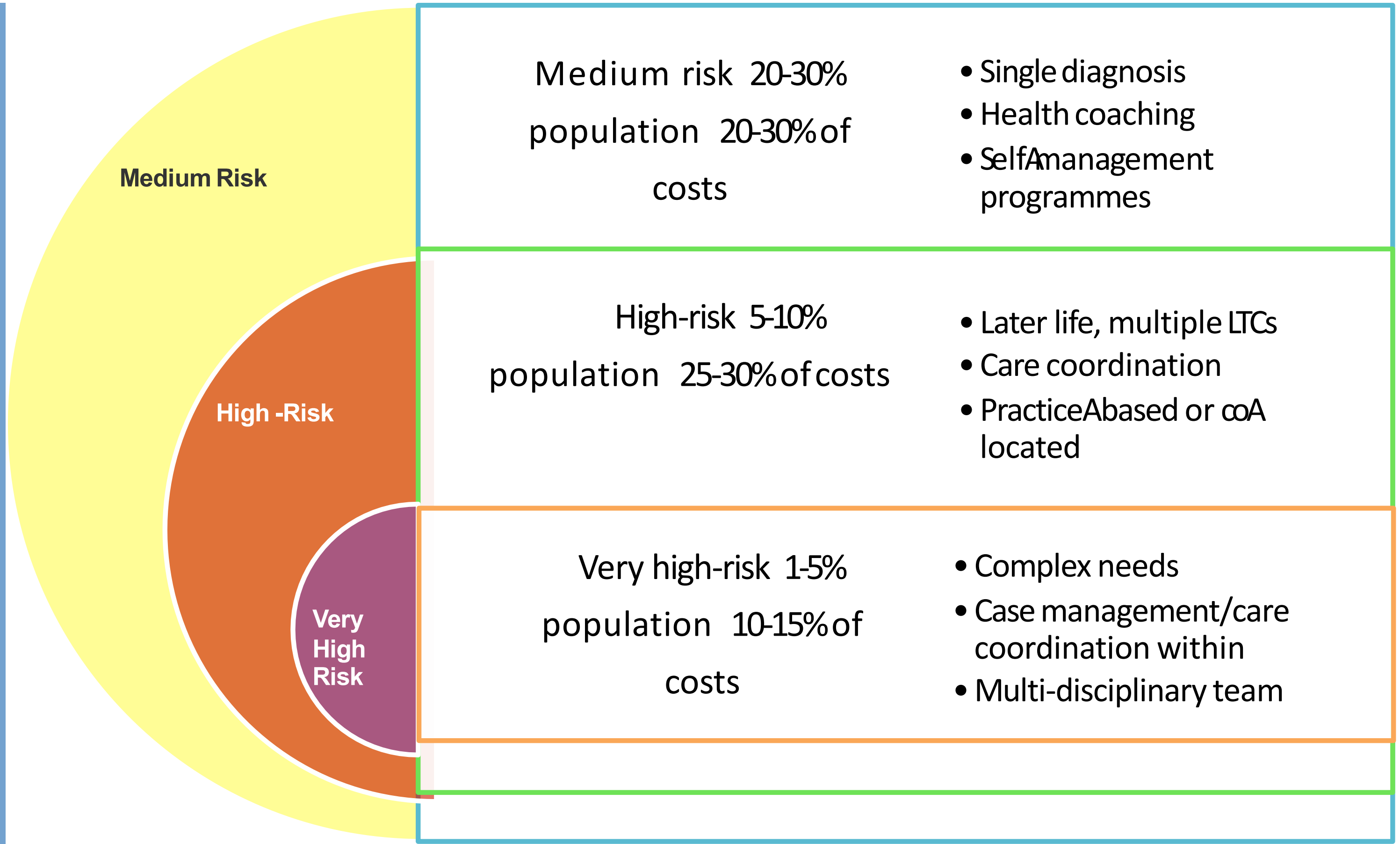
2.4 ACGs Supports an inclusive tailore approach

Some tools are focused on the needs of a small number of patients within a selective approach.

Whereas, a recent policy document from the Kings Fund described a 'house of care' which is inclusive of all patients with longAterm conditions.

ACGs provides the intelligence necessary to encompass the full range of need which the 'house of care' addresses. Hence it supports an inclusive model of care.

Patients by levels of need | **Tiers of service intervention**



2.5. What the clinical users say they require

Clinical staff need to be hands on with a risk stratification tool. This means it should be user-friendly and relevant

In our experience, clinical users have quite firm views about how best to achieve this.

The tool should identify patients who are not currently on my / our practice radar

The tools should be efficient in clinical time needed. We do not have a lot of time to plough through medical records only to find a few patients on the list requiring revisions to their treatment plans

- We need to incorporate social needs indicators

The patients identified should need revisions to their existing care plans and not include many others for whom everything is being done appropriately

2.6. Meeting user requirements – Functions of the predictive model

Through over 14 years of working with UK clinicians in case management, we have honed our ACG reporting designs to address clinical user requirements.

❖A range of predictors offer users choice to minimise the number of 'false positives'.

❖Users can subAset groups of patients on relevant criteria

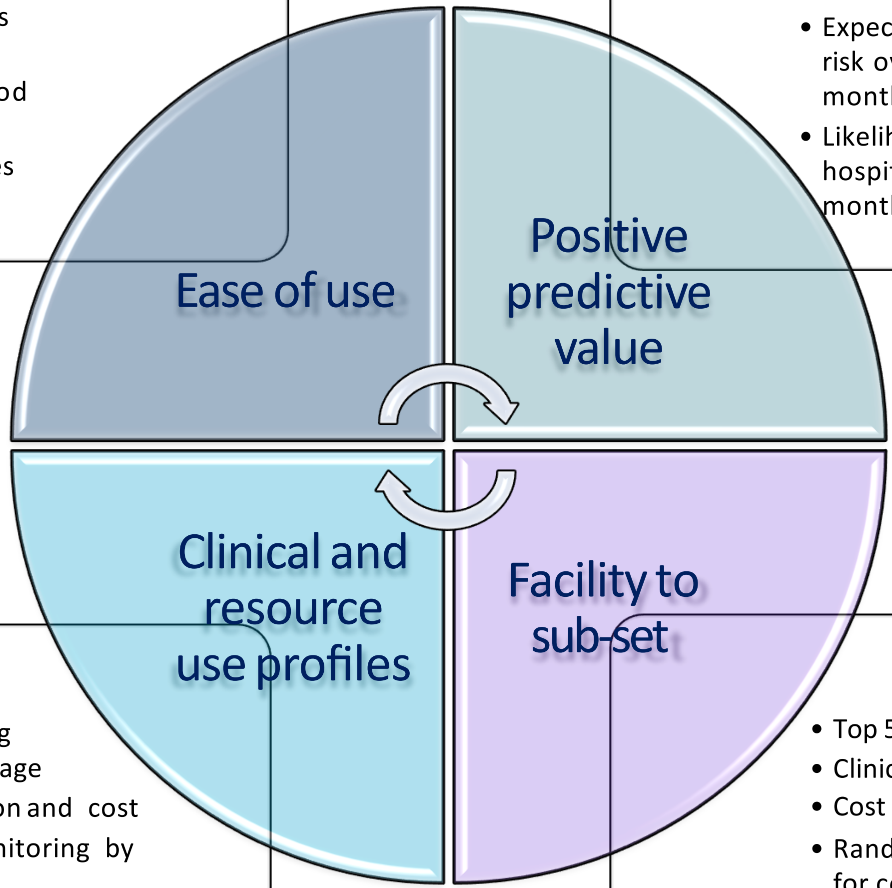
❖Clinicians can select on specific diagnoses, high hospital utilisation and capturethis data for outcomes monitoring

❖Reporting tool is designed by expert case managers who then lead clinical staff training.

- GPs and other doctors
- Case managers
- MD/ Neighbourhood teams
- Practice nurses

& managers

- Predictive high cost
- Expected to be high risk over the next 12 months
- Likelihood of hospitalisation in 6,12 months



- Major LTCs
- Corresponding pharmacy useage
- Prior utilisation and cost
- Outcome monitoring by intervention

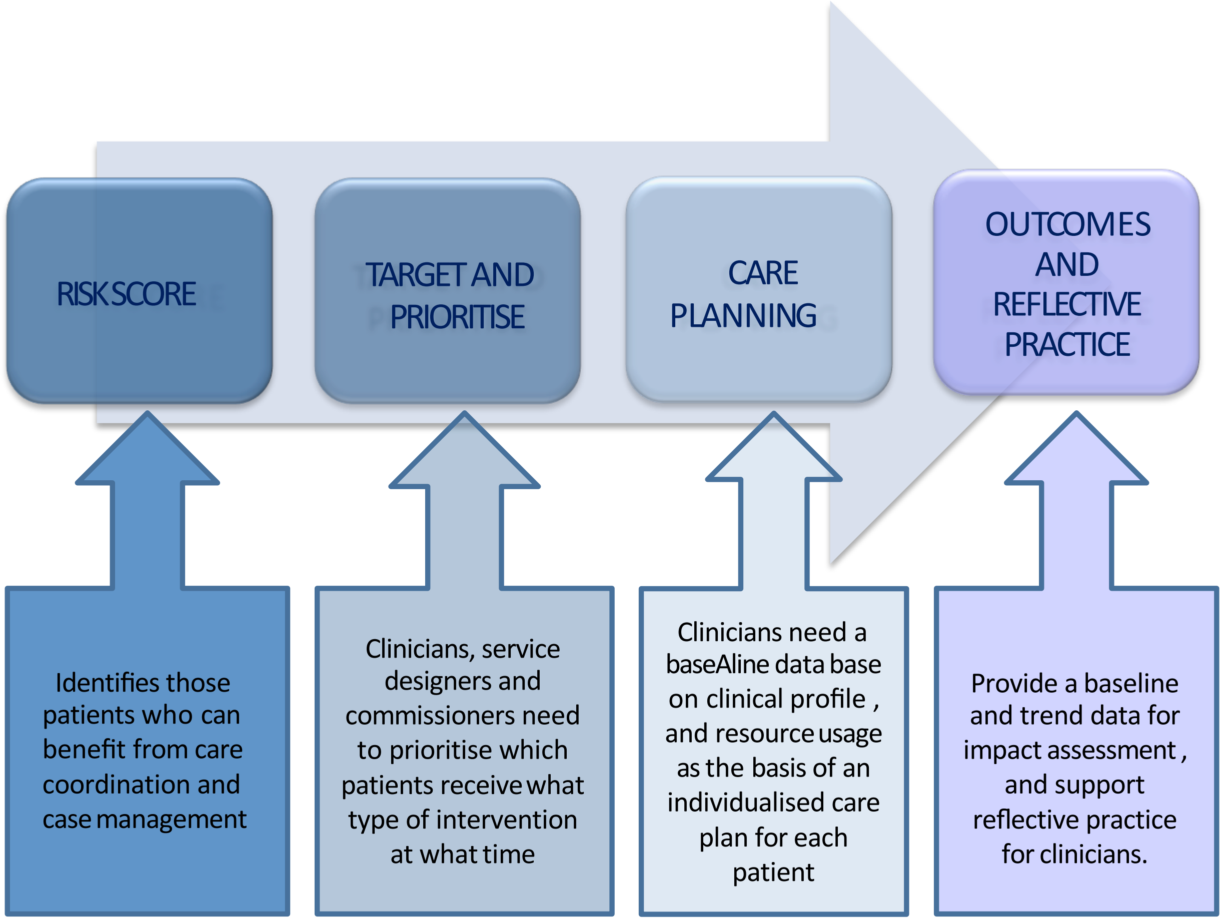
- Top 5, 3, 1%
- Clinical criteria
- Cost
- Randomised samples for control trials

2.7 Supporting the care coordination pathway

Risk stratification tools that only highlight relative risk can be of limited value to clinical staff.

The ConraneAIHSACG solutions support the entire care coordination patient pathway

Thus our reporting solution supports each of the four key stages of evidenceA based care coordination.



2.7.1 Prioritization

Here we explore how ACGs supports the first two stages in the pathway highlighted

- Risk scoring
- Prioritization

Stage 1 – Risk scoring

The ACG predictive model provides a list of patients by predictive risk factors as:

- The predictive relative risk or risk score to identify level 3, level 2 and level 1 patients
- The probability that the patient will be high cost
- The probability of the patient being hospitalised in 6 months and in 12 months

Stage 2 – prioritisation

Since there are unlikely to be sufficient resources at anyone time to manage all the patients, prioritisation is required. Hence our ACG reports allow clinicians to sort, group and filter on a range of clinically relevant parameters:

- Demographics data – age , sex, location
- Long Term Condition diagnoses
- Co-morbidities
- Costs and utilisation in the last 12 months

2.7.2 Screen shot of patients listed by ACG predictive markers (all data fictional)

Patients and ACG Results

To get highest Predicted Risk Score:
1. Click down-arrow on any measure. 2. Click remove sort. 3. Repeat and click filter - remove filter. 4. Click down-arrow on Predicted Risk Score 5. Click Sort
2. Note although this looks like a table, it is really a cube (like an excel pivot). Each of the dimensions (Patient ID, Age, ACG, etc) are treated as groupings.
To ensure the sorting works like a table, ensure each dimension's layout is set to flat using the down-arrow options

Practice

N81026 ▼

Measures by Patient ID and GP and Age and Ward Name

				Measures								
Patient ID	GP	Age	Ward Name	Total Cost	Current R... Risk Score	Predicted Risk Score	Probability Of High Cost	Hospital Domin... Morbidity Types	Chronic Condition Count	Probability High Pharmacy Cost	Probability IP Hosp	Probability IP Hosp ...
1798973	G8637365: GILES EA	93	Martlesham	10002	6.79	21.9	0.95	2	9	0.85	0.9	0.81
1807636	G8637365: GILES EA	77	Martlesham	7091	21.19	9.76	0.77	2	13	0.57	0.88	0.81
1815277	G8637365: GILES EA	80	Martlesham	9041	21.19	10.75	0.82	1	12	0.63	0.82	0.7
2037050	G8637365: GILES EA	91	Martlesham	15074	21.19	10.04	0.82	1	11	0.85	0.82	0.7
2039272	G9006689: LAWN JA	81	Egham Hythe	6284	6.79	7.01	0.56	0	6	0.29	0.82	0.7

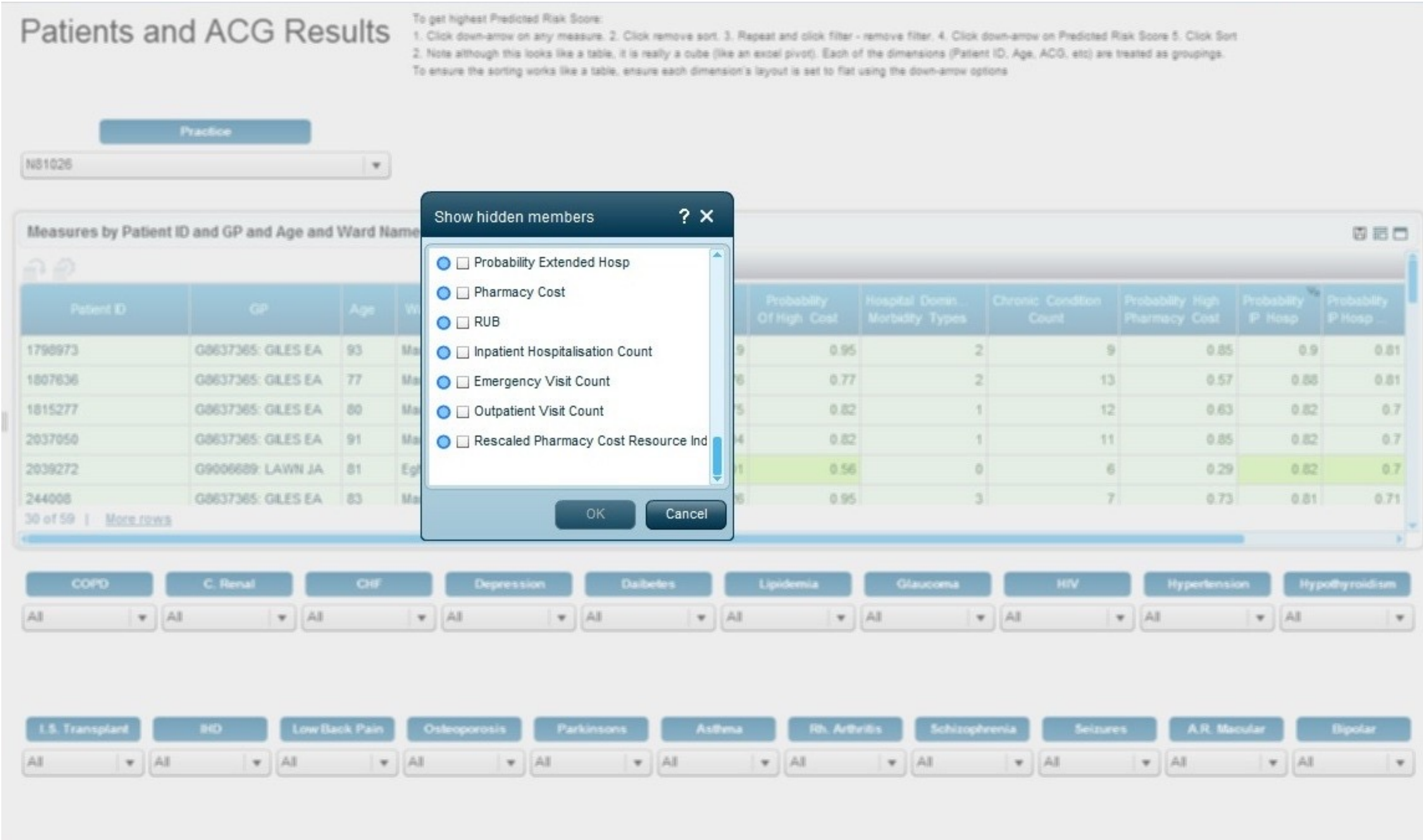
30 of 59 | More rows

COPD	C. Renal	CHF	Depression	Daibetes	Lipidemia	Glaucoma	HIV	Hypertension	Hypothyroidism
All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼

I.S. Transplant	IHD	Low Back Pain	Osteoporosis	Parkinsons	Asthma	Rh. Arthritis	Schizophrenia	Seizures	A.R. Macular	Bipolar
All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼	All ▼

THE USER CAN EASILY SORT AND SELECT PATIENTS ON A RANGE OF CLINICALLY-RELEVANT PARAMETERS

2.7.3 Selecting predictive high risk patients on utlisation andcost criteria
(all data fictional)



2.7.4. Selecting highArisk patients with hypertension, CHF and diabetes
(all data fictional)

Patients and ACG Results

To get highest Predicted Risk Score:
1. Click down-arrow on any measure. 2. Click remove sort. 3. Repeat and click filter - remove filter. 4. Click down-arrow on Predicted Risk Score 5. Click Sort
2. Note although this looks like a table, it is really a cube (like an excel pivot). Each of the dimensions (Patient ID, Age, ACG, etc) are treated as groupings.
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Practice

N81026

Measures by Patient ID and GP and Age and Ward Name

				Measures								
Patient ID	GP	Age	Ward Name	Total Cost	Current R... Risk Score	Predicted Risk Score	Probability Of High Cost	Hospital Domin... Morbidity Types	Chronic Condition Count	Probability High Pharmacy Cost	Probability IP Hosp	Prob.. IP H...
244008	G8637365: GILES EA	83	Martlesham	15683	9.86	26	0.95	3	7	0.73	0.81	0.71
1798973	G8637365: GILES EA	93	Martlesham	10002	6.79	21.9	0.95	2	9	0.85	0.9	0.81
2036611	G8637365: GILES EA	76	Martlesham	7411	13.89	15.83	0.95	1	12	0.99	0.63	0.57
1751970	G8911508: STEPHENS...	73	Egham Hythe	6804	21.19	14.97	0.95	4	10	0.79	0.73	0.58
1944542	G8637365: GILES EA	65	Martlesham	8106	13.89	14.88	0.95	3	6	0.99	0.77	0.66
2033544	G8637365: GILES EA	57	Martlesham	30345	21.19	13.31	0.95	0	9	0.87	0.69	0.56

30 of 115 | More rows

COPD	C. Renal	CHF	Depression	Daibetes	Lipidemia	Glaucoma	HIV	Hypertension	Hypothyroidism
All	All	BTH,ICD,Rx	All	BTH,ICD,Rx	All	All	All	BTH,ICD,Rx	All

I.S. Transplant	IHD	Low Back Pain	Osteoporosis	Parkinsons	Asthma	Rh. Arthritis	Schizophrenia	Seizures	A.R. Macular	Bipolar
All	All	All	All	All	All	All	All	All	All	All

2.7.5 Pathway stage two APatient profiles and careplanning

Stage 3 Care planning

Our ACG reports provide patients specific information which is needed to begin care planning. These are

- *Demographic* – Age, sex, location
- *A range of risk markers (*see adjacent box)
- *Utilisation of services and costs :* in previous 12 months (GP visits, number of medications, A&Evisits, outpatient visits and hospital episodes) and associated costs. For example, multiple medication prescriptions is a red flag for concordance problems or adverse medical reactions.
- *Diagnostic information* by longAterm condition and coA morbidity

The tool also minimises the need to access a patients clinical records at this point. An access window to the patient's encounter record for primary and secondary is advisable. Hence a clinician can ascertain if a patient with a diagnosis of COPD is being admitted to hospital respiratory medicine and thus may well be unstable.

Patient Clinical Profile

Long-term conditions

Common Condition Profile

Asthma		Chronic Renal Failure		Hypertension	BTH
Arthritis		Depression	Rx	Ischemic Heart Disease	ICD
Congestive Heart Failure	BTH	Diabetes	BTH	Low Back Pain	
COPD		Hyperlipidemia	Rx	Age Related Macular	
Bipolar Disorder		Glaucoma		HIV	
Hypothyroidism		Immun Supp Transplant	Rx	Osteoporosis	Rx
Parkinsons		Schizophrenia		Seizure Disorder	

blank=Not Present, Dx = ICD Indication, Rx = Rx Indication, BTH = Dx and Rx Indication

Utilisation and costs

Utilisation and Cost

Active Ingredients	24	Total Pharmacy Cost	£0
GP Attendances	18	Total GP Att Cost	£828
Outpatient Attendances	3	Total OP Cost	£308
Inpatient Attendances	10	Total IP Cost	£5,358
A&E Attendances	5	Total A&E Cost	£597
		Grand Total	**£7,091**

Risk markers

Special Markers		Predictive Values		Hosp Markers	
Major ADGs	4	Pred Risk Score	9.76	Prob IP Hosps	0.88
Chronic Conds	13	Prob High Cost	0.77	Prob IP Hosp 6mths	0.81
Hospital Dmnts	2	Prob High Pharm Cost	0.57	Prob Injury Hosp	0.10
Frailty Flag	Y	Rescaled Pharm Cost	6.03	Prob Hosp Extended	0.64

Social needs and risk factors can also be incorporated

2.8.1 Metrics for concurrent impact monitoring

All too oien care coordination initiatives fail due to lack of impact or outcomes data. This needs to change.

The table shows examples of relevant metrics on utilisation and costs of high-risk patients versus the population as a whole for one of our sample CCG localities

The table below, derived from the Johns Hopkins Adjusted Clinical Groups tool can be used for impact assessment by comparing:A

- Patients with a service intervention and those with a similar morbidity profile who not are in receipt of a specific service;
- Patients before, during and aier a case management or other care coordination programme;
- Comparing the impact of various programmes available locally to inform decisions about investment or dis-investment;
- Comparing subAgroups of patients by practice, practitioner, locality team etc.

To maximise the benefits to a care coordination programme, a risk stratification informatics tool needs to be able to generate this type of data. This should be collected concurrently and regularly (minimum every 3 months) for each patient. The tool should also support the aggregation or subAsetting of this data by programme intervention and patient group. (see section 4 on RiskStratification).

Group	Number	%	Avg.age	Per capita					
				GP visits	No. Meds	A nd E	OPD	Admits	Avg cost
All	65,535	100%	44.9	2.2	3.3	0.2	1.3	0.3	£525
All high risk	4,789	7.3%	69.6	6.9	12.9	0.7	6.1	1.9	£3,898
Very high risk	1,147	1.8%	69.0	8.2	13.5	1.5	9.8	5.2	£7,983

Data derived from the I.H.S ACG Solution

2.8.2 Metrics and reflective practice

Reflective practice should be a core component of any clinical process.

Surgeons are expected to routinely record and analyse their outcomes and feed this into clinical audit, practice development and productivity gain.

There are three main benefits when care coordinators do the same:

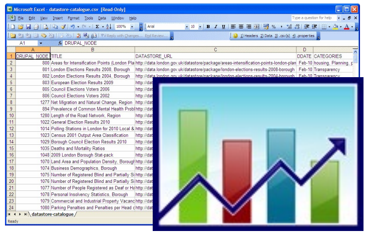
1) The practitioners are more likely to generate good outcomes if they see this data regularly and concurrently. Also the resultant positive feedAback is highly motivational.

2) There is no need for commissioners to rely solely on retrospective evaluations before deciding to invest or disA invest. This avoids decisionAmaking a i e r the event or ‘in the dark’.

Practice

Clinical Audit

ACGs data



3) Where independent, retrospective evaluations are commissioned, they will have access to a baseline and enough real data to undertake evaluation. The absence of this data has hampered evaluation of integrated care, leading frequently to inconclusive findings.

2.9 Identifying moderate risk patients

ACGs identifies patients with longA term conditions at moderate and low risk. This informs care planning, service planning and impact assessment for services such as health coaching and intelligent patients programmes. Services which support patients in self-management and concordance.

Diagnostic groups or EDCs can be analysed by relative risk. This patients with diabetes at moderate risk can be offered secondary preventive services such as health coaching etc.

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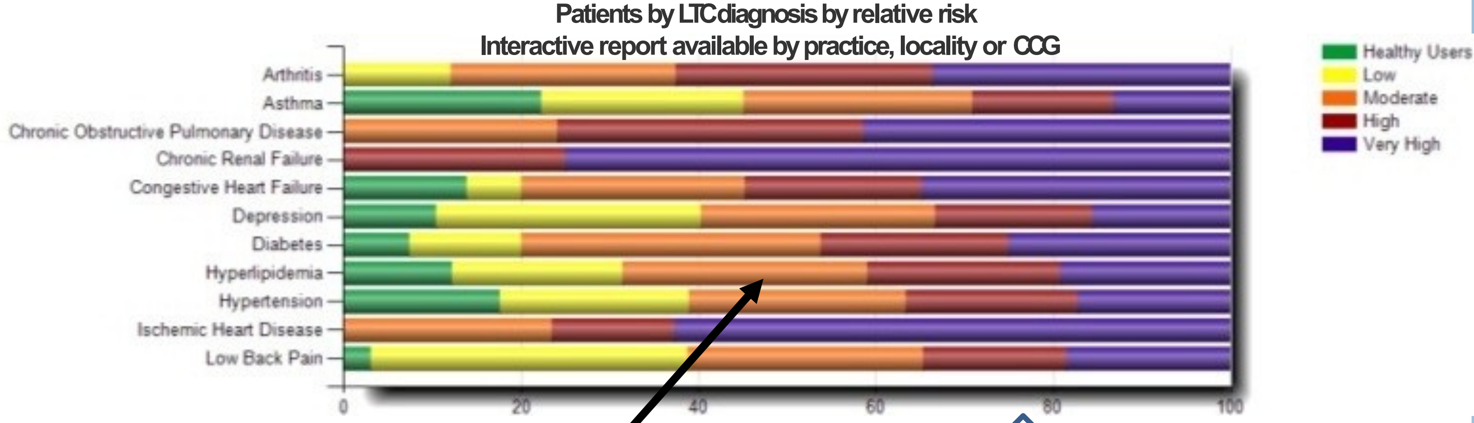
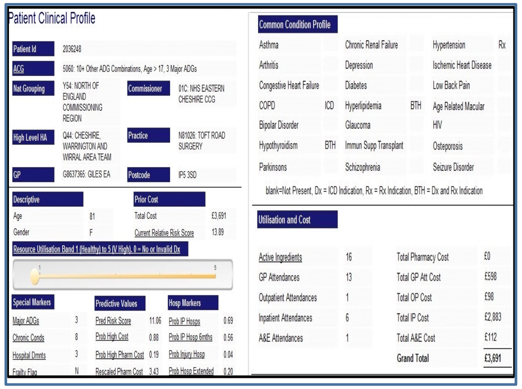


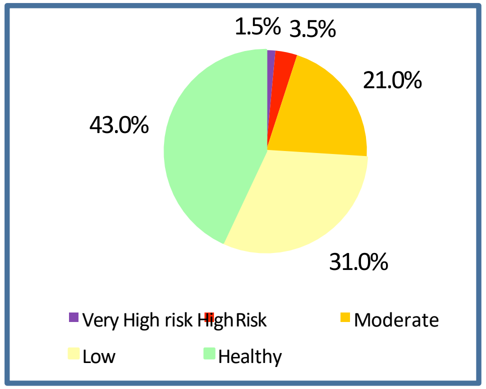
Level 1 patients with moderate risk

Prevalence of Level 1 LTC patients at low or moderate risk, by practice, locality. & CCG

Patient profile for care plan (see slide N)



Aggregate data for programme planning



2.10 Levels of aggregation and user access rights

The system has built in userAaccess screening. Hence only those authorised locally to see patient identifiable data will have access to this data. In the great majority of cases this is access is limited to the clinical staff in patients GP practices.

Aggregate data which meets information governance requirements is available at other levels in the local network. There are also data quality and completeness audit reports for informatics staff.

Practices

- All reports
- Inter practice comparisons
- Individual patient identifiable

Place

- Inter-practice comparisons
- Non-identifiable patientAlevel

ICSs

- Data quality and completeness by practice

Section 3 ACGs and caseAmix adjustment

Commissioners will need to setequitable hard budgets for constituent practices based on personA specific needs.

This requires adjusting budgets and resourceA management to account for legitimate caseAmix variations between practices.

CCGs will also needto develop personA specific budgets at practice level and manage the use of these budgets.

3.1. ACGs and case-mix in primary care resource use

ACGs measures morbidity and caseA mix.
This is one of the major factors affecting resource use and need in primary care.

Where practices show variations in resource use, case-mix needs to be taken into account. Once this is done, any remaining differences will be due to local practice variation

To derive hard budgets which are clinically acceptable to GPs and engage practices in constructive dialogue on resource useage, we need an approach which reflects differing needs at practice level. *Case:mix and resource use in primary care* A number of studies by the Primary Care Department at Imperial College have demonstrated the power of population caseAmix, measured by ACGs as a predictor of resource use in primary care. Interestingly the other major reason for variability in resource use is practice variation at the local level which is unrelated to relative patient need. ***Hence the ACG resource management approach has been designed to highlight variations in morbidity and thus indicate where there are also local variations in practice.***

- 'Morbidity/caseAmix explains almost six times more of the variation in general practice referrals (to hospital) than age and sex'
  - *Case:mix and variation in specialist referrals in general practice.* Sullivan CO, Omar RZ, Ambler G, Majeed A. Br J Gen Pract. 2005 Jul;55(516):529A33.
- Inclusion of a diagnosis based patient morbidity measure in prescribing models can explain a large amount of variability (in pharmacy costs), both between practices and within practices.
  - *A model based on age, sex, and morbidity to explain variation in UK general practice prescribing: cohort study* Rumana ZOmar, Caoimhe O'Sullivan, Irene Petersen, [3] Amir Islam, and Azeem Majeed,, BMJ. 2008; 337: a238.

3.2. ACGs Athe core case-mix measure

The building blocks of the ACG casemix system are 93 groups which give the system its name.

Diagnoses are subA grouped by likely clinical resource need .

Actual local costsare added to derive an average cost per ACG and thus complete the caseAmixmeasure

Each patient is ascribed 1 ACG. The 93 ACGs ascend according to patient complexity as illustrated in thetable

ACGs span the full spectrumof morbidity and healthneeds:

❖from patients who have no diagnosis or use of services on their records;

❖to so-called healthy users who may have had vaccinations screening or suffered a minor non-recurrent illness such as a cold;

❖right through to complex coAmorbid patients at the upper end of the need range.

Diagnoses are sub-grouped by likely clinical resource need A criteria such as

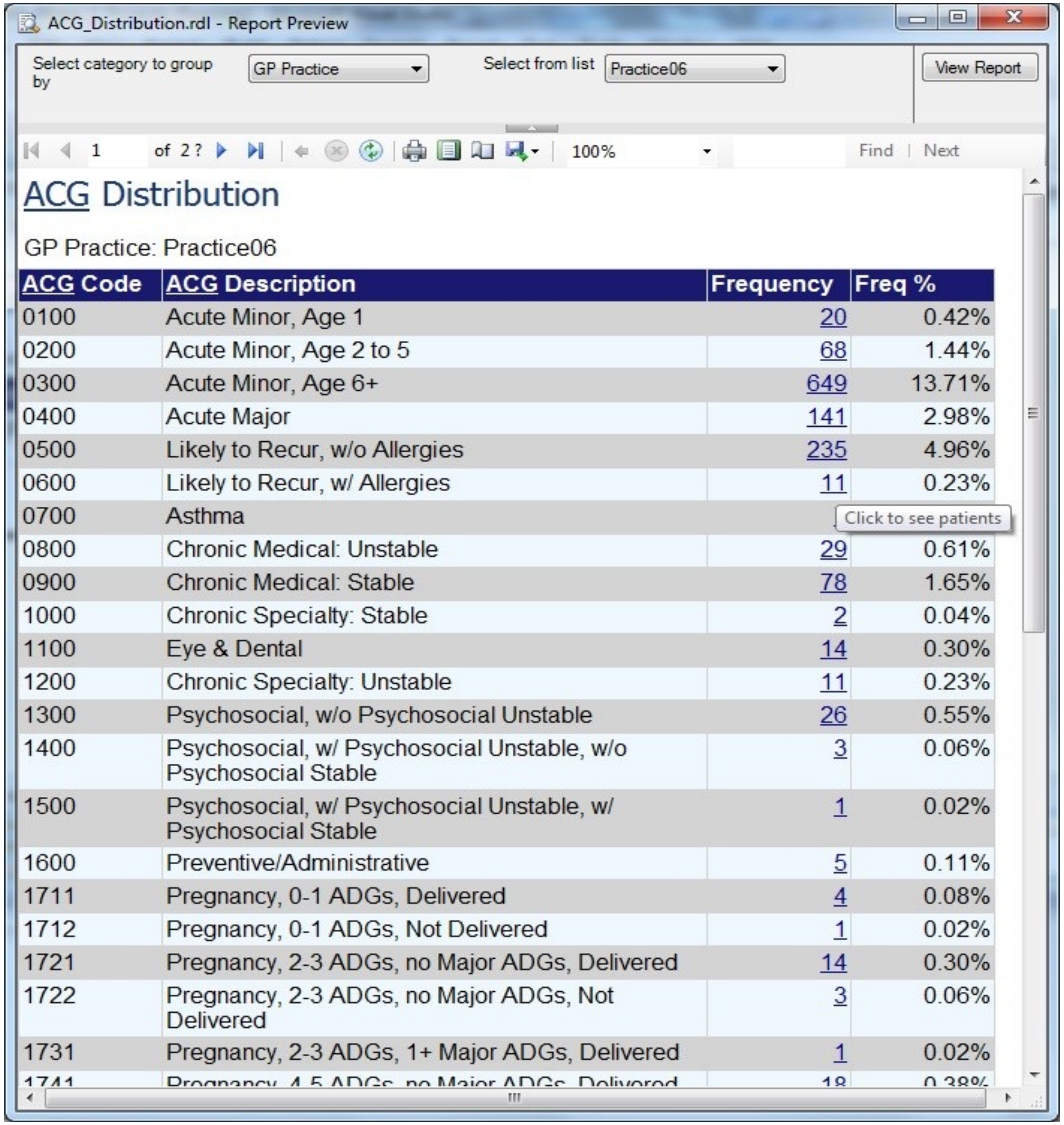
❖ *Duration (chronic or time: limited)*

❖ *Severity/stable/unstable*

❖ *Diagnostic certainty*

❖ *Aetiology*

❖ *Need for specialist care*



ACG Distribution

GP Practice: Practice06

ACG Code	ACG Description	Frequency	Freq %
0100	Acute Minor, Age 1	20	0.42%
0200	Acute Minor, Age 2 to 5	68	1.44%
0300	Acute Minor, Age 6+	649	13.71%
0400	Acute Major	141	2.98%
0500	Likely to Recur, w/o Allergies	235	4.96%
0600	Likely to Recur, w/ Allergies	11	0.23%
0700	Asthma		
0800	Chronic Medical: Unstable	29	0.61%
0900	Chronic Medical: Stable	78	1.65%
1000	Chronic Specialty: Stable	2	0.04%
1100	Eye & Dental	14	0.30%
1200	Chronic Specialty: Unstable	11	0.23%
1300	Psychosocial, w/o Psychosocial Unstable	26	0.55%
1400	Psychosocial, w/ Psychosocial Unstable, w/o Psychosocial Stable	3	0.06%
1500	Psychosocial, w/ Psychosocial Unstable, w/ Psychosocial Stable	1	0.02%
1600	Preventive/Administrative	5	0.11%
1711	Pregnancy, 0-1 ADGs, Delivered	4	0.08%
1712	Pregnancy, 0-1 ADGs, Not Delivered	1	0.02%
1721	Pregnancy, 2-3 ADGs, no Major ADGs, Delivered	14	0.30%
1722	Pregnancy, 2-3 ADGs, no Major ADGs, Not Delivered	3	0.06%
1731	Pregnancy, 2-3 ADGs, 1+ Major ADGs, Delivered	1	0.02%
1741	Pregnancy, 4-5 ADGs, no Major ADGs, Delivered	18	0.38%

3.3. Resource utilisation bands (RUBs)

The relative distribution by ACG analysis will differentiate populations by morbidity. 93 ACG categories can be subAgrouped into Resource Utilisation Bands or RUBs.

Hence for caseAmix adjustment using ACGs, Hamlet was right when hesaid: “Aye, there’s the RUB.”

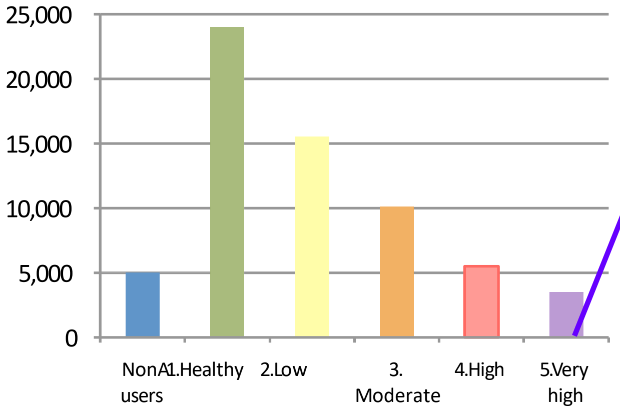
Grouping 93 ACGs into Resource Utilisation Bands (RUBs). There are number of ways of doing this. The most helpful in relation to resource management are *five* quintiles that group ACGs according to current patient costs. The model simply groups patients by ascending order of ACG complexity until it captures those who roughly account for 20% of the total population expenditure. Typically this outputs *six* groups. The first group is ‘non-users’ or people in the population for whom no diagnosis is recorded (no RUB ascribed). There are then 5 RUB groups.

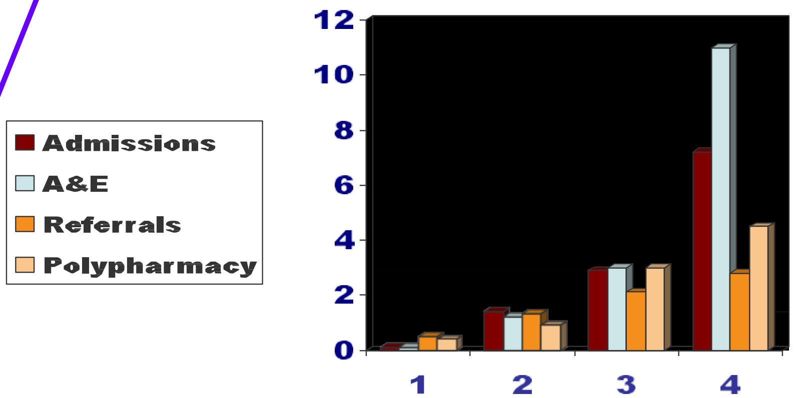
- **RUB 1 – Healthy users**
- **RUB 2 – Current low need/’impact’ patients**
- **RUB 3 – Moderate need**
- **RUB 4 – High need**
- **RUB 5 – Very high need**

Save 10% of the cost of this group
= £30 MILLION IN THIS CCG
5% of patients use 20 % of resources Average per patient annual cost of £12,500

Use of healthcare resources by R.U.B.
(RUB 4 and 5 combined in this analysis)

RUB distribution for a CCG locality of 65,000 population





3.4.1 Case mix comparisons (1) selected practice with locality and CCG averages

~~ACGs will answer the question 'is a practice using more resource because its patients are sicker or because it is not efficient – or both? In this report we are comparing the caseAmix of a practice with that of its locality and CCG respectively.~~

With just under 4.5% of patients in high and veryhigh RUBs Practice 09 has lower casemix than its locality average which shows nearly 9% in these two RUB groups

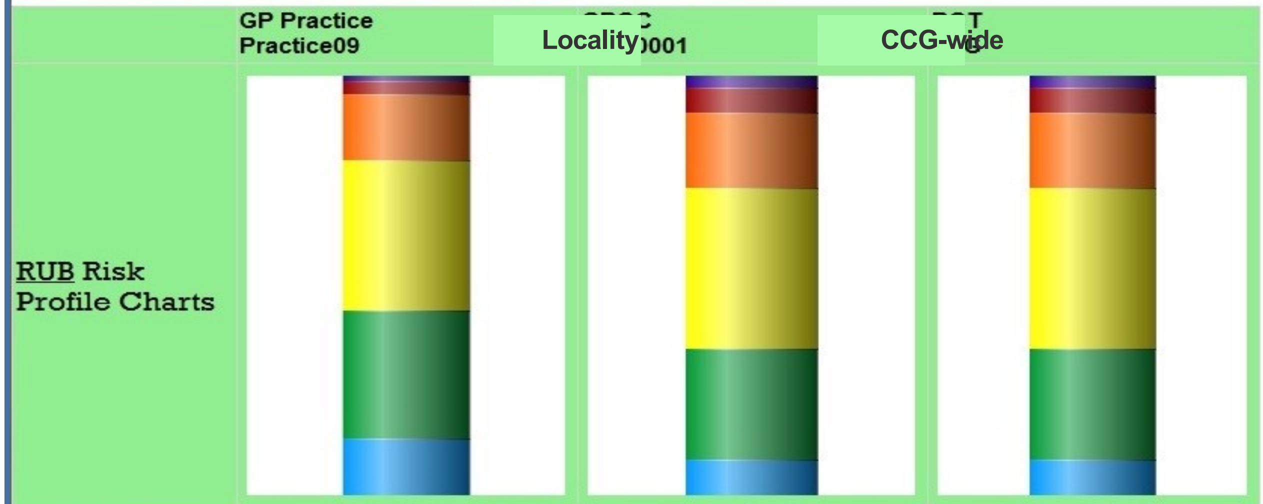
RUB_vs_Actual_Cost.rdl - Report Preview

Select Grouping: GP Practice
Pick from list: Practice09
Select RUB Band Set: RUB Bands from UK Feasability Studies using 2 PCTs

1 of 1 | 100% | Find | Next

RUB vs Actual Cost

GP Practice: Practice09
RUB Band Set: RUB Bands from UK Feasability Studies using 2 PCTs



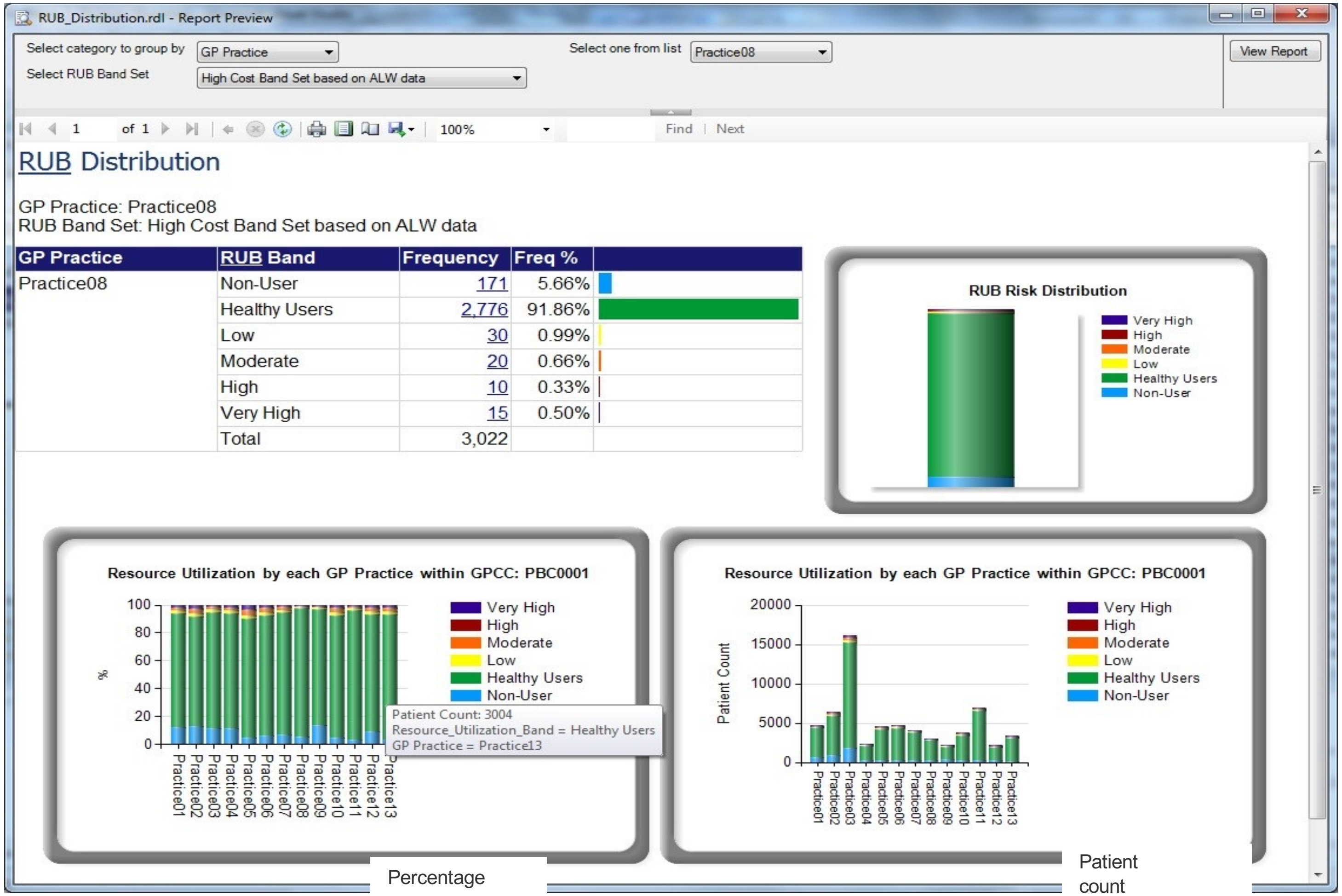
RUB Band	Average Cost	% Population	Average Cost	% Population	Average Cost	
Non-User	£0.00	13.48%	£0.00	8.36%	£0.0	
Healthy Users	£448.32	30.58%	£475.17	26.51%	£475.17	26.51%
Low	£817.63	35.92%	£911.08	38.50%	£911.08	38.50%
Moderate	£1801.91	15.66%	£1716.47	17.80%	£1716.47	17.80%
High	£3638.67	3.02%	£3110.69	6.09%	£3110.69	6.09%
Very High	£6772.41	1.35%	£4732.72	2.73%	£4732.72	2.73%

Patient Count: 5361
Resource_Utilization_Band = 0 - Non-User
PCT = 5HG
Click to view patients

3.4.1. Case mix comparisons (2) between practices

In this report we can see the relative casemix by practice (fictional data used). Practice 08 has the lowest case with the lowest number of patients in RUBs 4 and 5 (just under 1%).

This is both graphical and numeric illustration of the differences in morbidity between practice populations in a given locality. Generally speaking the differences or relativities will be greater with small practices than larger ones.



3.5.1 Risk Adjustment in Primary Care Budgeting (1)

However, we note from the Imperial College research, differences in resource use by GP practices is not just a feature of morbidity and local practice variation.

Hence by showing *actual cost to ACG case:mix adjusted cost*, we can adjust for morbidity and highlight those practices whose resource use seems to be significantly affected by local practice variation.

The headings on this table are explained on the next page

Practice 1 High cost and need but appears inefficient

Practice 3 Low cost, average need, appears efficient

1=average for all records

1	2	3	4	5	6	7	8
GP Practice	Patient Count	Total Actual Cost (£s)	Cost if average spend per patient (£s)	Ratio - Actual to Average	ACG case-	Ratio - Actual to ACG case-mix	ACG Adjusted Expected Cost (£s)
Practice 1	3,735	5,313,001	3,760,996	1.41	1.12	1.26	4,201,886
Practice 2	6,903	10,987,547	6,951,045	1.58	0.86	1.83	6,011,553
Practice 3	16,093	9,164,347	16,205,036	0.57	0.95	0.59	15,394,784
Practice 4	4,050	5,155,185	4,078,188	1.26	1.02	1.23	4,179,883
Practice 5	4,734	5,882,774	4,766,949	1.23	1.12	1.1	5,333,314
Practice 6	2,132	1,793,406	2,146,839	0.84	0.99	0.84	2,135,083
Practice 7	4,580	5,228,681	4,611,877	1.13	1.25	0.91	5,744,306
Practice 8	3,022	1,903,512	3,043,033	0.63	0.78	0.81	2,358,734
Practice 9	3,339	5,875,841	3,362,239	1.75	1.06	1.65	3,558,527
Practice 10	4,690	3,139,725	4,722,642	0.66	0.99	0.67	4,669,182
Practice 11	2,332	2,897,353	2,348,231	1.23	0.98	1.26	2,302,692
Practice 12	2,152	1,791,164	2,166,978	0.83	0.81	1,03	1,746,900
Practice 13	6,362	5,437,880	6,406,280	0.85	1.07	0.79	6,870,745
Total/avg	64,124	64,570,416	64,570,416	1	1	1	64,570,416

1. Ratio of Actual to overall average cost, and indicates whether the site is using more (>1) or less services than the average.

2. Index of the relative morbidity level of each practice's population as measured by ACGs (values >1.0=higher than average)

3.Relative Cost aier having adjusted for underlying caseAmix of the population. Values above and below 1.0 indicate variations in resource use due to local practice '

3.5.2 Risk Adjustment in Primary Care Budgeting (2)

This page elaborates the significance of the data in the previous slide.

- ❖ Column 1 show the practice identifier

- ❖ Column 2 The patient count or practice population

- ❖ Column 3 Total actual costs – shows the total expenditure per practice based on the cost items in the ACG dataAbase

- ❖ Column 4 Costs at average spend per patient (in green). This is a figure derived by assuming each patient within each practice costs the average for all patients in all 13 practices (just over £1000 per head)

- ❖ Column 5 From this we can derive an indicator Actual to Average that shows how actual spend per practices varies against the average. In this respect Practice 1 is high cost or 41% higher than average, whereas Practice 3 is low cost at only 57% of average

- ❖ Column 6 The ACG adjusted index show the caseAmix of the practice expressed as factor of 1 (which is the total average caseAmix). Hence Practice 1 has a 12% higher case mix than the average whereas Practice 3 is 95% of the average

- ❖ Column 7 Adjusts column 5 for ACG measured caseAmix. Practices above 1 are using resources over and above adjustment for caseAmix ie are relatively 'inefficient'. Practices below 1 are using resources below adjustment for caseAmix and are 'efficient'

- ❖ Column 8 using the ACG caseAmix index we can derive the ACG Adjusted Expected Cost that is what ACGs tells us to expect should be the expenditure of the practice once caseAmix is taken into account.

3.6 CaseAmix Adjusted Balanced scoreAcard

When benchmarking resource use in primary care it is necessary to adjust for caseA mix.

This principle can be expanded to consider specific resource items such as pharmacy, hospital referrals, admission rates, use of diagnostics etc.

This is illustrated by 3 practices in a southern CCG

GP Practice	Unadjusted realtive use actual/ average	ACG case-mix adjusted	Actual/ACG adjusted	Unadjusted realtive use actual/ average	ACG case-mix adjusted	ACG Adjusted Expected Cost (£s)
	Referrals to hospital			Secondary care costs		
A	0.98	0.92	1.2	0.96	0.75	1.28
B	1.27	0.99	1.29	0.8	0.82	0.97
C	0.86	1.33	0.66	1.2	1.6	0.75
	No of prescriptions per month			Inpatient admissions		
A	1.01	0.84	1.2	0.98	0.74	1.33
B	0.67	0.97	0.7	0.92	0.86	1.07
C	1.25	1.28	0.98	1.03	1.5	0.7
	Number of path. Tests			Outpatient attendances		
A	0.94	0.84	1.11	0.95	0.95	1.05
B	0.89	1	0.9	1.32	1.3	1.3
C	1.19	1.3	0.91	0.96	0.96	0.87

By developing a caseAmix adjusted balanced scorecard it becomes possible to compare resource use by practices in a more meaningful way. For example in the case of practice C in the above table, there was concern from central medicines management because the practice was spending 25% per head higher on average on pharmacy A as measured by the number of prescriptions. However when this comparison was caseAmix adjusted, the practice pharmacy use reverted to the average. Moreover this practice was also sending fewer patients to outpatients and admitting fewer patients than would have been expected given its caseAmix and admitting fewer patients to hospital. As a large health centre with 10 GPs including doctors with subAspecialization, Practice C was running a high quality, (relatively) low cost service. Hence the constant dialogue with the centre on pharmacy costs alone was unhelpful and frustrating for the practice.

This illustrates that comparing practices on a single resource category such as pharmacy without taking account of relative morbidity and other areas of expenditure can be misleading and usually generates 'more heat than light'.

3.7 ACGs and primary care budgeting in Sweden

The primary use of ACGs internationally is to adjust populations for case-mix in equitable resource management.

A number of countries have also adopted this approach. For example Sweden now employs ACGs in its resource allocation formula to primary care. We have seen how case-mix varies

- ACGs introduced for equitable resource allocation to primary care
- ACGs reduced the gaps between winners and losers versus approaches based on deprivation
- Clinicians preferred the clinically-driven approach

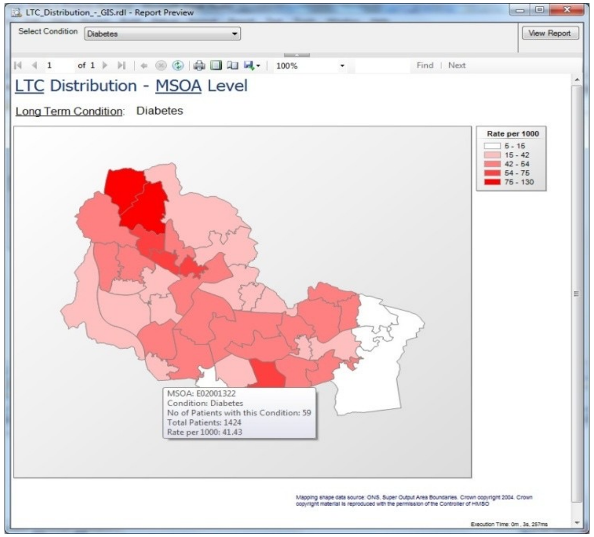
- ACGs was less contentious so implementation was facilitated
- Applying ACGs has led to improvements in the quality of coding in primary care

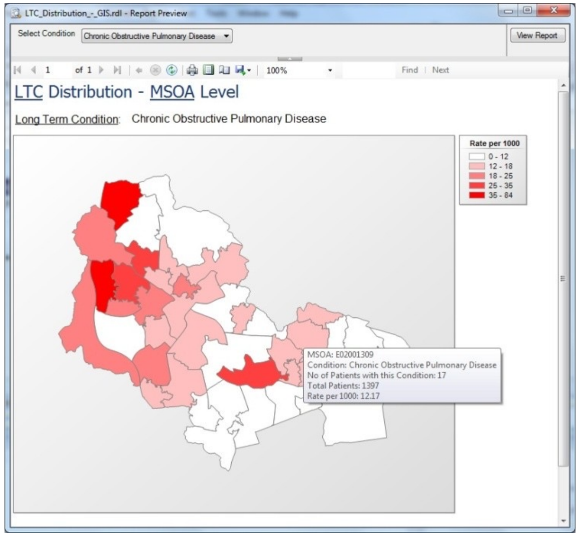
3.8 ACGs within iRIS interactive mapping and dashboards

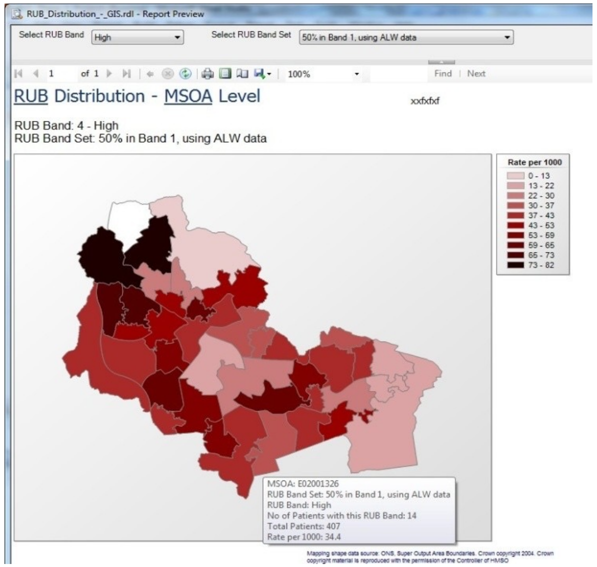
Within the ConraneA IHS iRIS version of ACGs we are able to link data to mapping and dashboard soiware.

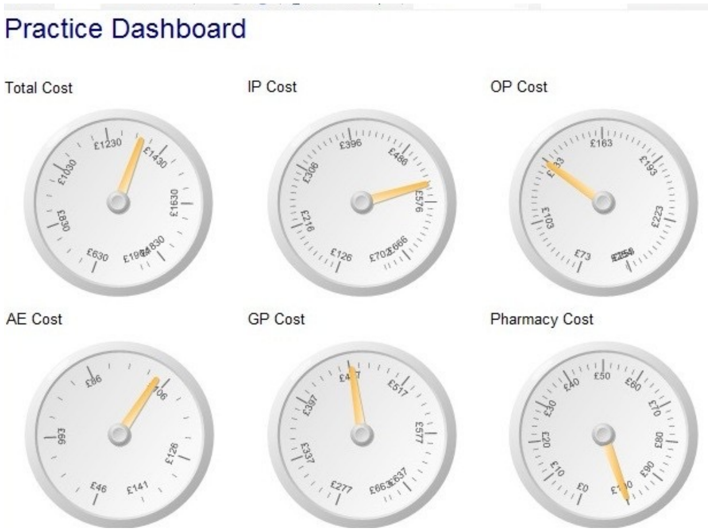
The maps are structured using super output areas so as to be of interest to public health. Both these graphical data presentations are interactive. Hence by clicking on a segment of the map, a list of these patients is generated.

Patient identifiable data is only available to those users with access rights (as locally determined).









Section 4 A Our ACG Development Team

Sue Barrett RN MSc (Training and connection to practice**)** Sue is an enthusiastic nurse with advanced nurse practitioner skills and prescribing skills who has worked as a care coordinator since 2005, and as a nurse for 37 years in the NHS. Sue's GP colleague commented "Sue *is like a GP Registrar and is a valuable member of our Practice and the service we provide to our local patients*" Sue is also a Professional Practice Teacher/Educator lecturing at the University of Surrey in care coordination, Health and Social care and Medicines Management. Her successful practice has led to her being invited to give presentations at national conferences by the RCN and the DH.. She has worked with IHS on two ACG deployments to lead clinical training and interpretation of data into practice.

Dr David Cochrane has extensive experience in whole system redesign and reform in the UK and on 4 continents. He implemented a combine risk tool in 200 practices beginning with Castlefields in 1999. In 2006 he began working with the Johns Hopkins Bloomberg School of Public Health and Imperial College to test the feasibility of ACGs in the NHS. This led to several live deployments since 2008. He has also led numerous successful care coordination projects in partnership with Imperial College. David has successfully adapted complex health technologies from the US to the UK and similarly taken best practices models from home and embedded them into the health systems of other countries.

Jayne Molyneux RN (Training and connection to practice) Having worked as a district nurse team leader, Jayne accepted the challenge in 1999 to become the first UK-practitioner in what is now called the Guided Care model at Castlefields Health Centre, Runcorn. Her success in that role led to her being engaged to develop other staff in the model working with I.H.S and subsequently as an independent consultant. Since 2008 she has widened her role to incorporate commissioning and provider development across long-term conditions, integrated care, demand management and QIPP programmes. She has worked with IHS on two ACG deployments to lead clinical training and interpretation of data into practice.

Our Technical Team

Christopher Dickson BSc. Chris Dickson specializes in Health Informatics, novel uses for information and methods of presentation of information to maximize impact. Chris has over 8 years senior NHS Information Management experience (to Assistant Director level), Chris is an accredited ACG informatics consultant. When at Tribal he designed the company's reporting solution for ACGs and has designed a bespoke reporting solution for Cheshire and Merseyside CSU.

Filipe McManus has 12 years experience working as a Business Intelligence (BI) Analyst for the NHS, specialising in a wide range of reporting software in use in the NHS. He has built various demand and capacity models for individual hospitals and for PCTs. He has a degree in Health informatics. He has worked extensively developing ACG System reports using the latest BI Tools.