This concept paper is in two parts that are intimately related. First is the breakdown of cardiac surgical results to assess the effects of each of the care components that makes up the care package of a patient’s experiences. Second, the way we assess risk in patients prior to surgery may potentially be improved if we change our mindsets from additive and logistic regression analysis and embrace modern software computer technology.

**PART 1: RISK ASSESSMENT OF MORTALITY IN CARDIAC SURGERY—A MARKER OF QUALITY, BUT WHOS?**

Quality in cardiac surgery can be defined by “the degree to which health care systems, services, and supplies for individuals and populations increase the likelihood for positive health outcomes and are consistent with current professional knowledge” (1).

Multiple components of patient care make up their care package that summates to create the quality of care that they received. With regard to the levels of care that a patient experiences the quality can be broadly broken down into institutional, departmental, surgeon, and procedure specific components (Figure 1). Each of these components can be further subdivided into numerous subdivisions.

Currently external scrutiny of quality in cardiac surgery is assessed by surgeon performance tables, and institutional results (2). Internal scrutiny of quality is assessed in numerous ways, but typically involves variables that are easy to measure, such as percentage compliance with care bundles and achievement of targets such as glucose or hematocrit range.

### Analysis Based on Current “Logistic Risk Assessment” Techniques

Risk assessment that is logarithmic in nature is typified by logistic Euroscore and the Southern Thoracic Society (STS) scoring system. Predicted logistic Euroscore mortality = $e (\beta_0 + \alpha_i X_i)/1 + e (\beta_0 + \alpha_i X_i)$ where $e$ is the natural logarithm, $\beta_0$ is the constant of the logistic regression equation = −4.79, $\beta_i$ is the coefficient of the variable $X_i$ in the logistic regression equation, $X_i = 1$ if a categorical risk factor is present and 0 if it is absent (3).

The constant, $\beta_0$ – a lumped constant, includes a number of terms that are not explicitly mentioned. These include institution and surgeon. Including institution and surgeon in the analysis as covariates would help to reveal the interaction between surgeon and institution, to help in quality improvement.
Analysis Based on Current “Additive Risk Assessment” Techniques

Risk assessment that is additive in nature is typified by additive Euroscore and the Parsonnet system (4). The constant for each risk factor in these systems has a component that reflects the average risk due to institutions and surgeons. Again, separation of additive value for an institution and the surgeon may help in quality improvement.

Why We Need to Analyze the Components of Cardiac Surgery Risk

Table 1 demonstrates how a failure to analyze the components of risk in cardiac surgery may result in a lost opportunity or failure to improve quality. An overall satisfactory mortality rate does not necessarily translate into “no room for improvement” practice. Combinations and permutations of surgeons and institutions demonstrate this:

**Scenario 1:** Table 1, Section A demonstrates that two surgeons working independently in two different units both could have identical mortality figures, for 100 identical coronary artery bypass graft (CABG) patients with a predicted risk of 2%. Under the current analysis of data no further action would need to be taken.

**Scenario 2:** If statistical analysis (Table 1, Section B) revealed that institution A was a risk factor by a factor of 3 (Institute 1.5%, Surgeon 0.5%) with regard to death and surgeon B was a risk factor by a factor of 3 (Institute 0.5%, Surgeon 1.5%), then potential targets for quality improvement exists. Root cause analysis would reveal – institute A and surgeon B issues.

**Scenario 3:** Table 1, Section C may demonstrate what happens if the “less good” surgeon from the “better” institute B goes to work at the “less good” institute A, a cause for concern, and a potential target for quality improvement. Root cause analysis would reveal – institute A and surgeon B issues.

**Scenario 4:** Table 1, Section D demonstrates that if the “better” surgeon from the “less good” institute A goes to work at the “better” institute B, there would be no cause for concern.

**Scenario 5:** In Table 1, Section E, the “better” surgeon going to work at the “better” institute B, may have worse outcomes as he has encountered the same issues surgeon B had. A potential target for quality improvement exists. Root cause analysis would reveal – institute A and surgeon A issues.

Separating Risk Due to Institution and Risk Due to the Surgeon

This is a very difficult task involving root cause analysis and statistical analysis. Root cause analysis may help to determine the role of the overlap areas of the three domains in Figure 1, as a contribution towards mortality. Currently the mode of death and root cause analysis is rarely published in cardiac surgery.

Learning from Engineering: Fourier Analysis of Cardiac Surgery Outcomes to Aid in Total Quality Management

This concept hinges on the appreciation that the mortality in cardiac surgery simplistically depends on constant (e.g., institutional, operation type) and variable factors...
(e.g., patient and surgeon factors). In addition it depends on the concept that the reference point is the “average.”

Separation of mortality figures by Fourier analysis (5) may help identify institutional, and surgeon performance that is missed when utilizing current risk models techniques such as Euroscore, STS risk model, and Cumulative Summation (CUSUM) curves.

Fourier analysis is a mathematical technique that can represent a variable function into a constant part and a series of sinusoidal terms (5). The mathematical derivation and utilization is shown in brief below.

For a periodic function \( f(x) \), it can be represented as a constant term and an expanding sine and cosine series—a Fourier series.

\[
F(x) = a_0/2 + \sum_{n=1}^{\infty} \left\{ a_n \cos(nx) + b_n \sin(nx) \right\}
\]

I.e. \( F(x) = \text{Constant Term} + \text{Variable Term} \)

where

\[
a_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(nx) dx, \quad n \geq 0
\]

\[
b_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(nx) dx, \quad n \geq 1
\]

\[
a_0 = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) dx
\]

The term \( a_0/2 \) in Equation 1 is the constant term, and equals the arithmetic mean, Equation 4.

Evaluation of the sinusoidal expansion is complex, and unnecessary for risk assessment, however the evaluation of the constant is elementary—it is simply the arithmetic mean, Equation 4. Fundamental to the concept of Fourier analysis as applied to cardiac surgery outcomes is the appreciation that the outcome of a patient is dependent on multiple factors, some of which vary, some of which don’t.

Any cardiac surgery procedure mortality has four components, institution (anesthetist, perfusionists, nurses….. health care assistants, cleaners, etc.), the operation, the surgeon, and the patient. Each institution will have an overall mortality rate, which may be high or low due to institutional and surgeon specific, or surgeon specific.

Any cardiac surgery procedure mortality has four components, institution (anesthetist, perfusionists, nurses….. health care assistants, cleaners, etc.), the operation, the surgeon, and the patient. Each institution will have an overall mortality rate, which may be high or low due to institutional and surgeon performance.

Mortality = \( F_{\text{Institutional}} + F_{\text{Operation}} + F_{\text{Surgeon}} + F_{\text{Patient Risk}} \) (5)

Therefore after substitution Mortality = \( (F_{\text{Institutional Risk}} + F_{\text{Institutional Procedural Risk}}) + (F_{\text{Procedure}} + F_{\text{Patient Risk}}) + F_{\text{Surgeon}} \) (7)

where:

- \( F_{\text{Institutional Risk}} \) - Institutional mortality rate for all cardiac surgery
- \( F_{\text{Institutional Procedural Risk}} \) - Institutional mortality rate for a specific procedure
- \( F_{\text{Procedure}} \) - National/international mortality for a procedure
- \( F_{\text{Patient Risk}} \) - Patient specific risk, e.g., Euroscore or STS Risk
- \( F_{\text{Surgeon}} \) - Surgeon risk for a specific procedure

All the factors are constant for a given procedure by a given surgeon other than \( F_{\text{Patient Risk}} \), hence the usual risk scoring systems only evaluate patient and operation type. The constant term in the Euroscore and STS risk model lumps the average of the \( F_{\text{Institutional Risk}} \), \( F_{\text{Institutional Procedural Risk}} \) and \( F_{\text{Surgeon}} \) together.

Depending on the dataset used it is possible to extract the factors lumped together by risk models. The evaluation of this concept is best shown by an example. Table 2 demonstrates how Fourier analysis based on the breakdown of overall mortality into its components can reveal differences in institution and surgeons. Negative values may seem counterintuitive, but they represent better than average performance, be it institutional, institutional operation specific, or surgeon specific.

An institution risk can be broken down by institutional system risk and operation specific risk. The two terms are not necessarily positively correlated. An institute may perform well with a high volume procedure such as CABG, but very badly in aortic surgery. An institutional mortality for cardiac surgery would miss this anomaly. As a corollary, a highly specialized unit may perform below average on straightforward CABG but excel in aortic surgery.

It is generally thought that high volume institutions have lower mortality rates. This technique allows identification of poorly performing surgeons working in good institutions and bad surgeons working in below average units.

It should be pointed out this is not a risk modeling tool but rather a technique to dissect out institutional and surgeon differences that are hidden when standard risk models and CUSUM curves are used (6). This technique can be equally applied to thoracic surgery and other areas as desired.

**Limitations**

This technique can only identify mortality causation for variables that are not co-segregated. For instance if a certain anesthetist only works with a certain surgeon, the effect of surgeon and anesthetist will be inseparable. The risk model accuracy used will be crucial to accurately interpret the institutional and surgeon risks.
Table 2. Demonstrates how Fourier analysis based on the breakdown of overall mortality into its components can reveal differences in institution and surgeons, despite an identical case mix.

<table>
<thead>
<tr>
<th>CABG Institute A</th>
<th>CABG Institute B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mortality = Constant ( F_{\text{Institutional Risk}} ) + Variable ( F_{\text{Institutional Procedural Risk}} ) + ( F_{\text{Patient Risk}} ) + ( F_{\text{Surgeon}} )</td>
<td>Mortality = Constant ( F_{\text{Institutional Risk}} ) + Variable ( F_{\text{Institutional Procedural Risk}} ) + ( F_{\text{Patient Risk}} ) + ( F_{\text{Surgeon}} )</td>
</tr>
<tr>
<td>National mortality rate 1.6%</td>
<td>National mortality rate 1.6%</td>
</tr>
<tr>
<td>( F_{\text{Procedure}} = +1.6 )</td>
<td>( F_{\text{Procedure}} = +1.6 )</td>
</tr>
</tbody>
</table>

Step 2 – Institute data

<table>
<thead>
<tr>
<th>Mortality = Constant ( F_{\text{Institutional Risk}} ) + Variable ( F_{\text{Institutional Procedural Risk}} ) + ( F_{\text{Procedure}} ) + ( F_{\text{Surgeon}} )</th>
<th>Institutional mortality rate 2%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( F_{\text{Institutional Risk}} + F_{\text{Institutional Procedural Risk}} = 2–1.6 = +0.4 )</td>
<td>Institutional mortality rate 1%</td>
</tr>
<tr>
<td>( F_{\text{Institutional Risk}} + F_{\text{Institutional Procedural Risk}} = 1–1.6 = -0.6 )</td>
<td></td>
</tr>
</tbody>
</table>

Step 3 – Patient risk

\[ F_{\text{Risk}} = F_{\text{Patient Risk}} + F_{\text{Procedure}} \]

Surgeon A to D patient mortality prediction \( F_{\text{Risk}} \) | Surgeon E to H patient mortality prediction \( F_{\text{Risk}} \)

\( F_{\text{Patient Risk}} = F_{\text{Risk}} - F_{\text{Procedure}} \) | \( F_{\text{Patient Risk}} = F_{\text{Risk}} - F_{\text{Procedure}} \)

\( = 3–1.6 = +1.4\% \) | \( = 3–1.6 = +1.4\% \)

Step 4 – Surgeon risk

<table>
<thead>
<tr>
<th>Mortality = Constant ( F_{\text{Institutional Risk}} ) + Variable ( F_{\text{Institutional Procedural Risk}} ) + ( F_{\text{Procedure}} ) + ( F_{\text{Surgeon}} )</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Surgeon A mortality rate 1%</td>
<td>Surgeon E mortality rate 1%</td>
</tr>
<tr>
<td>( F_{\text{Surgeon}} = -2.4 )</td>
<td>( F_{\text{Surgeon}} = -1.4 )</td>
</tr>
<tr>
<td>Surgeon B mortality rate 2%</td>
<td>Surgeon F mortality rate 2%</td>
</tr>
<tr>
<td>( F_{\text{Surgeon}} = -1.4 )</td>
<td>( F_{\text{Surgeon}} = -0.4 )</td>
</tr>
<tr>
<td>Surgeon C mortality rate 3%</td>
<td>Surgeon G mortality rate 3%</td>
</tr>
<tr>
<td>( F_{\text{Surgeon}} = -0.4 )</td>
<td>( F_{\text{Surgeon}} = +0.6 )</td>
</tr>
<tr>
<td>Surgeon D mortality rate 4%</td>
<td>Surgeon H mortality rate 4%</td>
</tr>
<tr>
<td>( F_{\text{Surgeon}} = +0.6 )</td>
<td>( F_{\text{Surgeon}} = +1.6 )</td>
</tr>
</tbody>
</table>

Step 5 – Statistical comparisons

The \( F_{\text{Risk}} \) for each surgeon should now be statistically compared, based on patient number. In the same way differences in patient and institute can be analyzed.

**PART 2: RISK ASSESSMENT IN CARDIAC SURGERY—HAS INFORMATION TECHNOLOGY LEFT BEHIND RISK MODELING IN CARDIAC SURGERY?**

**The Need for Change**

All scoring systems have limitations. Intuitively the risk of a procedure in a given patient is highly likely to be close to that of similar patients that have identical procedures. Numerous identifiable and non identifiable characteristics limit this approach, but are inherent limitations in any technique used.

Typical everyday cases when current scoring systems fail include:

**Example 1:** A 57-year-old gentleman for an aortic valve replacement (AVR) and mitral valve replacement (MVR) secondary to active endocarditis. The logistic Euroscore is 2.6\%. The national mortality for this in the United Kingdom is between 11\% (n = 45, age range 55–59) and 17\% (n = 280, all ages) (personnel communication, Ben Bridgewater, head database for UK cardiac surgery).

**Example 2:** A 57-year-old gentleman for an AVR, MVR, and tricuspid valve replacement with a moderate left ventricle. The logistic Euroscore is 2.6\%. The national mortality for this in the United Kingdom is 20\% (n = 242, all ages).

**Example 3:** A 57-year-old gentleman for removal of an incidental atrial myxoma, and mitral valve repair/replacement and closure of an inferior ischemic ventricular septal defect. The logistic Euroscore is 10\%, however this operation has not been done in the United Kingdom before.

**Example 4:** A 57-year-old gentleman with a previous aortic root replacement undergoing repeat aortic root replacement for a false left coronary artery aneurysm. The logistic Euroscore is 6.7\%, yet no double digit series exist in the literature.

**Current Risk Models and Databases**

A number of risk models are available to help cardiac surgeons around the world estimate risk for patients undergoing cardiac surgery, of which the Parsonnet (4), Euroscore (logistic and additive) (3), and Southern Thoracic Society (STS) (7) are the most widely used. Since the introduction of the STS adult cardiac surgery database in the United States [2009 5/id], the care quality commission/central cardiac audit database in the United Kingdom (CCAD) (8), and the Perfusion Downunder database, over one million cardiac operation procedures have been logged. Logging a case involves entry of pre operative risk factors, operative details, and post operative outcomes (i.e., alive or dead). Since the introduction of the STS database and CCAD, cardiac risk prediction may change forever.

The best predictor of what will happen in the future is what has happened in the past. This forms the basis of Bayesian risk analysis, which for the simple (five factor) and complex (nine factor) models in cardiac surgery have a receiver operating curve (ROC) value of .74 and .75, respectively (9). Euroscore has an ROC of .78, making Bayesian analysis comparable to any of the currently available risk models. Concerns about over complexity and inaccuracy have recently resulted in the description of the age, creatinine, ejection fraction scoring system, which has an ROC of .81, and only involves three risk factors (9).
**Why Current Models are Fundamentally Flawed**

The “risk factors” that contribute to the risk of dying from cardiac surgery are well known. However, the relative importance of these factors is debated (i.e., different coefficients in different models, and the interaction of risk factors is unclear). The interaction between variables has been simplified as either additive (Parsonnet or additive Euroscore) or logarithmic (STS and logistic Euroscore). Both techniques rely on a simple mathematical relationship between the risk variables, (Equations 8 and 9).

$$
\text{Additive risk} = \text{Risk Factor 1} + \text{Risk Factor 2} + \ldots + \text{Risk Factor } n \tag{8}
$$

$$
\text{Logistic risk} = \text{Risk Factor 1} \times \text{Risk Factor 2} \times \ldots \times \text{Risk Factor } n \tag{9}
$$

where Risk Factor consists of the factor or its logarithm, and a coefficient.

As the exact relationship between the risk factors and mortality after cardiac surgery is not known, it is impossible to develop an exact model, hence the use of receiver operating curves. Some examples from human physiology where we know the mathematical models will help demonstrate the inaccuracy of blind application of additive or logistic analysis are shown in Appendix 1.

**Using Information Technology**

A 70-year-old gentleman with hypertension, hypercholesterolemia, and moderate left ventricular dysfunction who presents for a CABG is likely to be very similar to a very large number of patients who have already undergone CABG, whose outcomes are known. The STS database holds CABG mortality figures on 245,132 patients (7) between the ages of 65 and 75, thus the patient can be told their predicted risk with very small error bars of uncertainty. A limitation of all current risk prediction models is that they do not include error bars for the predicted risk they calculate.

Information technology (IT) has advanced enormously, as has computer power, enabling large databases to be queried very quickly and produce their results in numerical or graphical format on web pages in real time. This process uses technology such as Structured Query Language (SQL) (10) and active server pages (11) (asp or aspx extension you see in the internet browser address bar).

**Matching Patients**

Any risk matching/modeling results are only as good as the technique involved in their production. With regard to SQL matching the following may represent a first methodology outline.

1. **Univariate analysis:** This is based on traditional Bayes analysis. Bayes analysis has a number of statistical limitations of non normalized data, however should it be used as a technique for risk factor matching based in ascending order of risk importance then these limitations do not exist.

<table>
<thead>
<tr>
<th>Risk Factor</th>
<th>Criteria</th>
<th>Death</th>
<th>Survival</th>
<th>Odds Ratio</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td></td>
<td>2.60%</td>
<td>97.40%</td>
<td>.027</td>
<td>−36.3</td>
</tr>
<tr>
<td>Age</td>
<td>&lt;56</td>
<td>9.00%</td>
<td>20.80%</td>
<td>.4</td>
<td>−8.4</td>
</tr>
<tr>
<td></td>
<td>56–60</td>
<td>9.50%</td>
<td>16.80%</td>
<td>.6</td>
<td>−5.7</td>
</tr>
<tr>
<td></td>
<td>61–65</td>
<td>17.70%</td>
<td>21.10%</td>
<td>.8</td>
<td>−1.7</td>
</tr>
<tr>
<td></td>
<td>66–70</td>
<td>22.90%</td>
<td>20.90%</td>
<td>1.1</td>
<td>.9</td>
</tr>
<tr>
<td></td>
<td>71–75</td>
<td>22.90%</td>
<td>14.30%</td>
<td>1.6</td>
<td>4.7</td>
</tr>
<tr>
<td></td>
<td>&gt;75</td>
<td>18.00%</td>
<td>6.00%</td>
<td>3.0</td>
<td>10.9</td>
</tr>
<tr>
<td>Body surface area</td>
<td>&lt;1.70</td>
<td>12.60%</td>
<td>8.30%</td>
<td>1.5</td>
<td>4.1</td>
</tr>
<tr>
<td>(m$^2$)</td>
<td>1.70–1.89</td>
<td>25.70%</td>
<td>20.50%</td>
<td>1.3</td>
<td>2.3</td>
</tr>
<tr>
<td></td>
<td>1.90–2.39</td>
<td>42.40%</td>
<td>50.20%</td>
<td>.8</td>
<td>−1.7</td>
</tr>
<tr>
<td></td>
<td>&gt;2.39</td>
<td>4.40%</td>
<td>7.30%</td>
<td>.6</td>
<td>−5.2</td>
</tr>
<tr>
<td>Diabetes</td>
<td>No</td>
<td>66.60%</td>
<td>73.60%</td>
<td>.9</td>
<td>−1</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>18.80%</td>
<td>15.00%</td>
<td>1.3</td>
<td>2.2</td>
</tr>
<tr>
<td>Hypertension</td>
<td>No</td>
<td>42.90%</td>
<td>48.40%</td>
<td>.9</td>
<td>−1.2</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>51.40%</td>
<td>46.00%</td>
<td>1.1</td>
<td>3.1</td>
</tr>
<tr>
<td>Left main stem disease</td>
<td>No</td>
<td>51.40%</td>
<td>61.00%</td>
<td>.8</td>
<td>−1.7</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>14.40%</td>
<td>9.60%</td>
<td>1.5</td>
<td>4</td>
</tr>
<tr>
<td>Ejection fraction</td>
<td>&gt;50%</td>
<td>37.50%</td>
<td>60.10%</td>
<td>.6</td>
<td>−4.7</td>
</tr>
<tr>
<td></td>
<td>30–49%</td>
<td>30.10%</td>
<td>24.70%</td>
<td>1.2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&lt;30%</td>
<td>21.90%</td>
<td>5.50%</td>
<td>4</td>
<td>13.8</td>
</tr>
<tr>
<td>Priority</td>
<td>Elective</td>
<td>44.50%</td>
<td>65.80%</td>
<td>.7</td>
<td>−3.9</td>
</tr>
<tr>
<td></td>
<td>Urgent</td>
<td>29.30%</td>
<td>23.70%</td>
<td>1.2</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td>Emergency</td>
<td>14.90%</td>
<td>2.50%</td>
<td>6</td>
<td>17.8</td>
</tr>
<tr>
<td>Renal</td>
<td>Dialysis</td>
<td>1.80%</td>
<td>.40%</td>
<td>4.4</td>
<td>14.8</td>
</tr>
<tr>
<td></td>
<td>Raised</td>
<td>9.30%</td>
<td>3.70%</td>
<td>2.5</td>
<td>9.1</td>
</tr>
<tr>
<td></td>
<td>creatinine None</td>
<td>31.10%</td>
<td>.34%</td>
<td>.9</td>
<td>−9</td>
</tr>
<tr>
<td></td>
<td>Previous operations None</td>
<td>78.40%</td>
<td>.86%</td>
<td>.9</td>
<td>−9</td>
</tr>
<tr>
<td>Operations</td>
<td>≥1</td>
<td>12.10%</td>
<td>3.70%</td>
<td>3.2</td>
<td>11.7</td>
</tr>
</tbody>
</table>

Individual Bayes analysis will need to be performed for all cardiac procedures independently (e.g., CABG, AVR, MVR, etc), as risk factors in one category may not be significant in others. Table 3 demonstrates the Bayes analysis for the UK data for isolated CABG.

2. **Centile range and binary variable selection:** Risk factors can then be matched in descending order of importance based on Bayes analysis odds ratios. Discrete variables such as diabetes or no diabetes have to be matched exactly. Continuous variables will need to be matched by centile, starting with ±5% centiles from data risk factor variable. Some risk factors are not normally distributed hence this approach. Figure 2 demonstrates the variation in normality of cases from a single institute in the United Kingdom.

3. **Matching and error bar calculation:** Using SQL, a query can then be produced to search the relevant cardiac surgery database to find patients that match the above criteria. Mortality and morbidity can be reported. The error bars, based on number of matched can then be calculated.

4. **Morbidity:** The morbidity (e.g., renal failure, prolonged ventilation, resternotomy rate, stroke, and deep sternal wound infection) of the matched patient group could then be retrieved to inform clinicians and patients of the possible complications and their relative risk of developing them.
Figure 2. Distribution of risk factors in a typical United Kingdom unit. For a given patient risk factor these graphs can be used to calculate the range for the variable that would result in a ±5% range.
5. **Long-term survival**: In countries like the United Kingdom, which have national death registries, long-term survival can also be calculated for the matched group. Life tables apply to the general population, not to patients who have undergone cardiac surgery.

6. **Narrowing of centile range to decrease error bar size**: When a large number of matches are returned by the SQL query (e.g., 75-year-old males undergoing CABG), the centiles for each of the Bayes risk factors can be narrowed to increase the clinical applicability.

### Advantages of SQL Risk Assessment over Standard Modeling

This technique has a number of potential advantages over standard risk models:

1. It requires no modeling or estimations, the basis of risk modeling.
2. It automatically updates itself as cases are continually added, so as medical care slowly improves, this technique automatically adapts to it so it does not require updating, the equivalent of remodeling.
3. It eliminates errors due to co-segregating variables.
4. It provides up-to-date regional data for strategic planning in real time.
5. It enables the collection of the risk profile of patients who are deferred or declined—data that is currently unavailable.
6. It could be used as a medico legal record that appropriate risk assessment has been carried out for a particular case.
7. It is able to inform clinicians which patients will potentially have a long length of stay, chance of a short length of stay, permanent stroke, prolonged ventilation, deep sternal wound infection, renal failure, and reoperation for bleeding and should be discussed at multidisciplinary meetings, and who is likely to have a very poor 1-, 3-, and 5-year survival—by linking with the national strategic tracking service.
8. It is possible for this technique to quote risk outcomes for an individual institute and even for individuals for any given cardiac procedure.
9. It adds or removes patient variables to the database as research into risk factors progresses, is very easy, and again involves no remodeling.
10. It could be used as part of consultant revalidation, and
11. It is a very cheap solution to an ongoing problem.

### Limitations

Limitations exist in any system. This potentially new technique still needs clinical judgment in its use. An 85-year-old third time redo aortic, mitral, and tricuspid valve replacement with CABG may have rarely been performed in the past so any model will be inaccurate. Logistic and additive Euroscore would predict a risk of 19%, which is clearly incorrect. The IT solution proposed above would tell you that only two people with the same risk profile have had the procedure and the error bar on the CCAD data, one who lived one who died, would be 35% with a mortality of 50%, making clinical judgment more important than any prediction technique.

### Other Risk Factors

At present, other non quantifiable risk factors such as systemic vasculitis, thrombocytopenia, anemia, von Willebrand disease, sarcoidosis, hemolytic anemia, etc do not score on any risk or quality modeling. The number of conditions is so large as to be impossible to quantify and list. Future cardiac databases may serve cardiac surgery better by having a domain “other risk factors” that are free text fields, that after peer review of the extraneous factor are used to eliminate or incorporate that patient from current risk assessment. In this way “difficult decision” patients need not worry about being turned down due to surgeon securitization.

### CONCLUSION

Focusing on the individual elements of the team that deliver cardiac surgical care may help identify factors other than “surgeon” related issues that contribute towards mortality and morbidity. Reassessment of the techniques that are used to predict risk of mortality and morbidity due to cardiac surgery by embracing modern software tools may help in producing a more robust prediction tool than current additive and logistic regression analysis.

### REFERENCES

APPENDIX 1

The following examples demonstrate how additive and logistic models can be correct or fundamentally flawed depending on the equation linking the covariates. The examples were deliberately chosen from medicine, where the relational formula was known. In risk modeling the formula linking covariates and mortality is unknown. However, a simple additive or logistic approach is highly unlikely to be correct with so many variables when these techniques are inaccurate on simple known three or four variable biological models.

Example 1. Value of Additive Analysis – Mean Blood Pressure

Blood Pressure (BP) = Diastolic pressure + 1/3 Pulse pressure (10)

BP = 1/3 (systolic pressure) + 2/3 (diastolic pressure) (11)

Log BP = constant + log systolic pressure + log diastolic pressure (12)

An additive analysis would reveal an exact match, Equation 11, for mean blood pressure based on diastolic and systolic blood pressure. A logistic analysis, Equation 12, would be completely wrong.

Example 2. Value of Logistic Analysis – Flow down the Internal Mammary Artery

Flow in a tube is well known to be determined by Poiseuille’s law, Equation 1, which depends on radius (r), viscosity (η), and length (L). An additive analysis would lead to Equation 14. The ROC would be so poor no one would adopt the model. A logarithmic analysis would yield Equation 15. This would have a very good ROC as it is an exact match.

Flow = constant + η + L + r (14)

Log Flow = log (8/π) + log η + log L − 4.log r (15)

However, should the interaction between the variables be more complicated neither technique will be correct.

Example 3.

Scenario 1: Blood pressure equals the product of cardiac output (CO) and systemic vascular impedance (SVI), Equation 16. Additive analysis, Equation 17, would be highly inaccurate, but logistic analysis, Equation 18, would be an exact match.

BP = CO*SVI (16)

BP = CO + SVI (17)

Log BP = log CO + log SVI (18)

Scenario 2: Cardiac output equals stroke volume (end diastolic volume (EDV) – end systolic volume (ESV)) multiplied by heart rate (HR). Both additive analysis, Equation 20, and logistic analysis, Equation 21, would be inaccurate.

BP = (EDV − ESV)*HR*SVI (19)

BP = EDV + ESV + HR + SVI (20)

Log BP = log EDV + log ESV + log HR + log SVI (21)

However, if the terms EDV and ESV are kept together, logistic analysis will be an exact match, Equation 22.

Log BP = log (EDV − ESV) + log HR + log SVI (22)

Scenario 3: From scenario 1, SVI is calculated from systemic vascular resistance (SVR) and systemic vascular reactance (SVX). Both additive analysis, Equation 24, and logistic analysis, Equation 25, would be inaccurate.

BP = CO*(SVR^2 + SVX^2)^(1/2) (23)

BP = CO + SVR + SVX (24)

Log BP = log CO + log SVR + log SVX (25)

However, if the terms SVR and SVX are kept together, logistic analysis will be an exact match, Equation 26.

Log BP = log CO + ½*log (SVR^2 + SVX^2) (26)