# TRANSACTIONS OF SOCIETY OF ACTUARIES 1983 VOL. 35 

# TOWARD COMPUTERIZED UNDERWRITINGA BIOLOGICAL AGE MODEL 

ROBERT L. BROWN AND K. S. BROWN*


#### Abstract

This paper presents a theoretical basis for a computerized methodology for estimating biological age-a measure of time to death. The authors then discuss their attempts to reproduce the human underwriting of one life insurance company using a computerized methodology.


## I. INTRODUCTION

Competition within the life insurance industry seems to increase consistently with time. In order to achieve the lowest possible costs for their products, life insurance companies must pursue diligently all possible avenues for reducing expenses.

In the past thirty years, computer technology has assisted greatly in reducing costs in many insurance company operations. This paper will assert that it is now feasible to computerize much of the underwriting process, and, with continuous monitoring of the computerized system, not sacrifice any significant level of underwriting accuracy. This would lower underwriting costs significantly and shorten the time from application to issue of the policy.

## II. A BIOLOGICAL AGE MODEL

In determining the premium to be paid for life insurance, or a life annuity, the actuary is concerned with time to death. This is clear from the mathematical formulation of the net single premium functions:

For life insurance:

$$
\begin{equation*}
\bar{A}_{x}=\int_{0}^{x} v^{\prime}, p_{x} \mu_{x+1} d t \tag{1}
\end{equation*}
$$

[^0]For life annuities:

$$
\begin{equation*}
\bar{a}_{x}=\int_{0}^{x} \bar{a}_{त}, p_{x} \mu_{x+1} d t . \tag{2}
\end{equation*}
$$

Several decades ago, the underwriter carefully analyzed each application according to his best estimate of time to death before assigning an appropriate premium to it.

Over the years, as rates of mortality declined, and as the cost of medical information and the underwriting process rose, more policies were issued on a nonmedical basis. For these policies, the only factors affecting the premium are sex and chronological age, or time since birth. Chronological age may be an important factor in predicting time to death, but it has been argued [3] that a high correlation with chronological age is neither a necessary nor a sufficient condition for an index that accurately measures time to death.

Instead, several biostatisticians have turned to a concept called biological age as a superior way to present, in a single parameter, the best estimate for time to death. If a risk is assigned a biological age $x$, that risk has a life expectancy, $\dot{e}_{x}$, which corresponds to the life expectancy of the average member of the defined group whose chronological age is $x$. That is, someone assigned biological age 45 will have the same life expectancy as the average of a group of people whose chronological ages are 45 . Therefore a biological age model is nothing more than a disguised statement of life expectancy. The reason for this method of statement will be explained later.

Several studies on the estimation of an index of biological age are listed in the References.

The Framingham Study of $1973,{ }^{1}$ an epidemiological study of cardiovascular disease, has been used in the development of the biological age model. The general framework of this study can be described as follows. At the start of the study period, measurements on $k$ variables are taken on $n$ individuals deemed free from disease. After a period of $m$ years, the individuals are reexamined and the $n_{1}$ individuals who have developed the disease in the interim are noted. Based on these data, it is desired to estimate $P\left(x_{1}, x_{2}, \ldots, x_{k}\right)$, the probability that an individual with measurements ( $x_{1}, x_{2}, \ldots, x_{k}$ ) will develop the disease in $m$ years. A model to estimate this probability, suggested by Cornfield [7], has been used extensively in the analysis of such data: If $P\left(x_{1}, \ldots, x_{k}\right)$ represents the

[^1]probability of developing the disease given measurements ( $x_{1}, \ldots, x_{k}$ ) at the beginning of the study, then
\[

$$
\begin{equation*}
P\left(x_{1}, \ldots, x_{k}\right)=\frac{p f_{1}\left(x_{1}, \ldots, x_{k}\right)}{f\left(x_{1}, \ldots, x_{k}\right)} \tag{3}
\end{equation*}
$$

\]

and

$$
\begin{equation*}
1-P\left(x_{1}, \ldots, x_{k}\right)=\frac{(1-p) f_{0}\left(x_{1}, \ldots, x_{k}\right)}{f\left(x_{1}, \ldots, x_{k}\right)} \tag{4}
\end{equation*}
$$

where $f_{0}\left(x_{1}, \ldots, x_{k}\right)$ and $f_{1}\left(x_{1}, \ldots, x_{k}\right)$ represent the initial densities of characteristics in the populations subsequently found to be healthy and diseased, respectively; $f\left(x_{1}, \ldots, x_{k}\right)$ represents the unconditional distribution; and $p$ represents the unconditional probability of developing the disease. Thus from equations (3) and (4),

$$
\begin{equation*}
P\left(x_{1}, \ldots, x_{k}\right)=\left[1+\frac{(1-p) f_{0}\left(x_{1}, \ldots, x_{k}\right)}{p f_{1}\left(x_{1}, \ldots, x_{k}\right)}\right]^{-1} . \tag{5}
\end{equation*}
$$

If $f_{0}$ and $f_{1}$ are assumed to be multivariate normal with the same variancecovariance matrix $\Sigma$ and means $\mu_{0}$ and $\mu_{1}$, respectively, then

$$
\begin{equation*}
P\left(x_{1}, \ldots, x_{k}\right)=\left[1+\exp \left(-\alpha-\sum_{i=1}^{k} \beta_{i} x_{i}\right)\right]^{-1}, \tag{6}
\end{equation*}
$$

where ${ }^{2}$

$$
\begin{equation*}
\alpha=-\frac{1}{2}\left(\mu_{1}-\mu_{0}\right)^{\prime} \Sigma^{-1}\left(\mu_{0}+\mu_{1}\right)-\log [(1-p) / p] \tag{7a}
\end{equation*}
$$

and

$$
\begin{equation*}
\left(\beta_{1}, \beta_{2}, \ldots, \beta_{k}\right)=\left(\mu_{1}-\mu_{0}\right)^{\prime} \Sigma^{-1} . \tag{7b}
\end{equation*}
$$

When the unknown parameters are replaced by their estimates, the resulting estimates of $\alpha$ and $\beta_{i}$ are

$$
\begin{align*}
& \hat{\alpha}=-\frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k}\left(\tilde{X}_{1 j}-\bar{X}_{0 j}\right) S_{i j}^{-1}\left(\bar{X}_{1 i}+\bar{X}_{0 i}\right)-\log \left(n_{0} / n_{1}\right),  \tag{8a}\\
& \hat{\beta}=\sum_{j=1}^{K}\left(\bar{X}_{1 j}-\bar{X}_{0,}\right) S_{i j}^{-1} . \tag{8b}
\end{align*}
$$

[^2]These may be recognized as the estimated linear discriminant function coefficients with $\alpha=c-\log \left(n_{0} / n_{1}\right)$ (see, for example, [12]). Thus, under the assumptions of multivariate normality with equal variance-covariance structure in both populations, the model and estimates of the parameters are well defined. Of course, the imposed structure is rarely justified since the measured variables will include binary data (such as positive family history of heart disease) and markedly nonnormal data (such as number of cigarettes smoked per day). However, the form of the model (see Fig. 1) is intuitively a reasonable one for estimating risk, since it ranges from zero to one and increases rapidly over the middle portion of the range. Hence, the model attempts to find the linear function of $\left(x_{1}, \ldots, x_{k}\right)$ that places the healthy individuals at the "zero" end of the curve and the diseased individuals at the "one" end. Interactions among risk factors can be modeled by including appropriate product terms in the set ( $x_{1}, \ldots$, $x_{k}$ ).

Estimates of $\alpha$ and $\left(\beta_{1}, \ldots, \beta_{k}\right)$ when assumptions of normality are not made (but the form of the model is assumed) may be obtained by maximizing the likelihood function

$$
L\left(\alpha, \beta_{1}, \ldots, \beta_{k}\right)=\prod_{j \in U_{0}}\left[1-P_{j}\left(x_{1}, \ldots, x_{k}\right)\right] \prod_{j \in U_{1}} P_{j}\left(x_{1}, \ldots, x_{k}\right)
$$



Fig. 1.-Graph of the logistic function used to estimate the risk of developing cardiovascular disease; that is, the probability $P$ is given by $P=[1+\exp (-L R)]^{\prime}$, where $L R$ is the logit of risk.
for $\alpha$ and ( $\beta_{1}, \ldots, \beta_{k}$ ), where $U_{0}$ and $U_{1}$ represent the sets of individuals in the healthy and diseased populations respectively, and $P_{,}\left(x_{1}, \ldots, x_{k}\right)$ represents equation (6) evaluated at the values of ( $x_{1}, \ldots, x_{k}$ ) observed for the $j$ th individual. The maximum likelihood estimates often do not differ significantly from the linear discriminant coefficients and the latter often are used because their calculation does not involve iteration.

Such problems often involve a large number of independent variables. It is common to attempt to determine an "optimal" subset of these variables; that is, a relatively small number of the independent variables that may predict risk nearly as well as the entire set.

The importance of any variable, say the lth (for example, systolic blood pressure), for predicting risk may be investigated by maximizing $L_{1}\left(\alpha, \beta_{1}\right.$, $\left.\beta_{2}, \ldots, \beta_{l}=0, \ldots, \beta_{k}\right)$. The ratio $-2 \log \left[L_{i}(\bar{\alpha}, \bar{\beta}) / L(\hat{\alpha}, \hat{\beta})\right]$, where $(\bar{\alpha}, \tilde{\beta})$ is the vector of estimates under the second model and $(\hat{\alpha}, \hat{\beta})$ is the vector of estimates under the full model, is asymptotically $\chi_{1}^{2}$ under the hypothesis $\beta_{1}=0$, and large values of this quantity indicate evidence against the hypothesis that the lth variable is unimportant in predicting the development of the disease, after adjusting for other variables.

These types of tests form the basis for stepwise procedures for model building. That is, variables can be entered into models one at a time so that each successive variable entered is the one that increases the likelihood function the most, given the variables previously accepted. The procedure stops when no variable that is not in the model increases the likelihood appreciably. Such procedures can be combined with variable elimination procedures, which remove variables one at a time until the removal of any variable in the model would decrease the likelihood appreciably. These stepwise procedures have been used extensively to try to determine "optimal" subsets of independent variables; however, they recently have come into considerable criticism (e.g., [9] and [10]). With the development of high-speed computers and numerical methods, it is possible to screen a great many of the models very quickly and determine which might be suitable candidates for consideration for an optimal model. The program SMOD, as described in [10], does this model screening, and was used in the analysis described below.

One advantage of developing adequate models of risk, other than the ability to test quantitatively for significant predictor variables, is that they may be used to prepare convenient summary tables such as Table 1. Such tables allow a physician to inform the patient of his personally estimated risk of developing disease and to determine which factors are elevating this risk. Further, when this is combined with a table such as Table 2, the physician is able to present the individual's risk relative to individuals

TABLE I
Probability per 1,000 of Developing
Cardiovascular Disease* in the Next Eight Years by Specified Characteristics

| Serum <br> Cholesterol. | Probability per 1,000 for 45-Year-Old Male ${ }^{+}$ |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Systolic Blood Pressure |  |  |  |  |  |  |
|  | 105 | 120 | 135 | 150 | 165 | 180 | 195 |
|  | Nonsmokers |  |  |  |  |  |  |
| 185 | 22 | 27 | 35 | 43 | 54 | 68 | 84 |
| 210. | 28 | 35 | 43 | 54 | 68 | 84 | 104 |
| 235. | 35 | 44 | 54 | 68 | 84 | 104 | 129 |
| 260. | 44 | 55 | 68 | 85 | 105 | 129 | 158 |
| 285. | 55 | 68 | 85 | 105 | 129 | 158 | 192 |
| 310. | 68 | 85 | 105 | 130 | 158 | 192 | 232 |
| 335. | 85 | 105 | 130 | 159 | 193 | 232 | 277 |
|  | Smokers |  |  |  |  |  |  |
| 185. | 38 | 47 | 59 | 73 | 91 | 112 | 138 |
| 210 | 47 | 59 | 73 | 91 | 113 | 138 | 169 |
| 235. | 59 | 74 | 91 | 113 | 139 | 169 | 205 |
| 260. | 74 | 92 | 113 | 139 | 170 | 206 | 247 |
| 285. | 92 | 113 | 139 | 170 | 206 | 247 | 293 |
| 310. | 114 | 140 | 170 | 206 | 248 | 294 | 345 |
| 335. | 140 | 171 | 207 | 248 | 295 | 356 | 401 |

Source.-Framingham Study, sec. 28, The Probability of Developing Certain Cardiovascular Diseases in Eight Years at Specified Values of Some Characteristics (Washington, D.C.: United States Department of Health, Education, and Welfare, 1973).

* In the Framingham definition, cardiovascular disease is considered to have developed if there is a definite manifestation of coronary heart disease, intermittent claudication, congestive heart failure, or cerebrovascular accident in the absence of a previous manifestation of any of these diseases or rheumatic heart disease.
$\dagger$ Probabilities are estimated using the model

$$
P\left(x_{1}, \ldots, x_{8}\right)=\left[1+\exp \left(-\hat{\alpha}-\sum_{i=1}^{8} \hat{\beta}_{i} x_{i}\right)\right]^{-1}
$$

where $\hat{\alpha}=-19.7709560$ and

| $i$ | $\dot{\beta}_{i}$ | $x_{i}$ | i | $\dot{\beta}_{i}$ | $x_{i}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | . 3743307 | age | 5 | . 5583013 | cigarettes (0, nonsmoker; 1, smoker) |
| 2 | -. 0021165 | (age) ${ }^{2}$ |  | 1.0529656 | LVH-ECG (0, none; 1, present) |
| 3 | . 0258102 | SC | 7 | . 6020336 | GI (0, absent; 1, present) |
|  | . 0156953 | SBP | 8 | -. 0003619 | SC times age |

experiencing "average" (or perhaps, with some modification to the table, "ideal") risk.
Table 2 is based on Robbins and Hall's [13] approach to preventive medicine, called "health hazard appraisal." In this system, an individual's chances of dying from a number of diseases are computed, based on his physiological measurements, lifestyle, and so forth. These are combined and the composite risk is compared with the risk of death experienced by an "average" member of the population. The individual's appraised age, the age of the average individual with same risk of death, is obtained in this way together with recommendations aimed at reducing the ap-

TABLE 2
Appraised Age of Individual with Specified Characteristics

| Serum Cholesterol. | Appraised Age of 45-Year-Old Male* |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Systolic Blood Pressure |  |  |  |  |  |  |
|  | 105 | 120 | 135 | 150 | 165 | 180 | 195 |
|  | Nonsmokers |  |  |  |  |  |  |
| 185 | 36 | 37 | 39 | 40 | 42 | 44 | 46 |
| 210. | 37 | 39 | 40 | 42 | 44 | 46 | 49 |
| 235. | 39 | 40 | 42 | 44 | 46 | 49 | 52 |
| 260. | 40 | 42 | 44 | 46 | 49 | 52 | 55 |
| 285. | 42 | 44 | 46 | 49 | 52 | 55 | 60 |
| 310. | 44 | 46 | 49 | 52 | 55 | 60 | 70 |
| 335. | 46 | 49 | 52 | 55 | 60 | 70 | 73 |
|  | Smokers |  |  |  |  |  |  |
| 185. | 39 | 41 | 43 | 45 | 47 | 50 | 53 |
| 210. | 41 | 43 | 45 | 47 | 50 | 53 | 56 |
| 235. | 43 | 45 | 47 | 50 | 53 | 56 | 63 |
| 260. | 45 | 47 | 50 | 53 | 56 | 63 | 71 |
| 285. | 47 | 50 | 53 | 56 | 63 | 71 | 74 |
| 310. | 50 | 53 | 56 | 63 | 71 | 74 | 75 |
| 335. | 53 | 57 | 63 | 71 | 74 | 75 | 77 |

Note.-The appraised or risk age is the age of the average Framingham Study (1973) male with the equivalent risk of developing cardiovascular disease in the next eight years by the same characteristics as specified in Table 1 (GI absent, LVH-ECG negative).

Source.-Brown and Forbes [3].

* Calculations were based on the following average risks (see sec. 28 of the Framingham Study)

| Age | 35 | 40 | 45 | 50 | 55 | 60 | 65 | 70 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| Risk per 1,000 | 18 | 41 | 75 | 115 | 159 | 193 | 212 | 229 |

and risks of approximately 0 per 1,000 and 1,000 per 1,000 at ages 0 and 105, respectively. The appraised age was estimated by an average quadratic logistic interpolation procedure; results at ages over 70 were obtained by extrapolation from the arbitrary values given above, and should be treated with caution.
praised age. Since most persons appreciate the consequences of being, say, five years older than they are chronologically, the message is presented more effectively than if the same information were expressed as a probability. In this way, individuals appraised as being "older" than their chronological age may be encouraged to reduce factors that are elevating risk, and those appraised as "younger" may have their positive lifestyles reinforced.

A similar "health hazard appraisal" model is used by Health and Welfare, Canada, in their "Evalu-Vie" program. The input to the computer program consists of coded answers to the risk factor inquiry detail shown in the Appendix.

Thus, a biological age index may be seen as a function of a set of observable quantities, each of which makes an important contribution to the prediction of age at death, years until death, or some other measure stratifying the population by risk subgroups.

A biological age index, $y$, then may be written in the form

$$
y=f(x, V, I, \Delta)
$$

where $y$ represents, for example, age at death, years until death, reduction in optimal lifespan, or an individual's appraised or risk age; $x$ is the chronological age; $V$ represents the additional contribution (adjusted for chronological age and other variables in the function) of the absolute level of a set of variables such as blood pressure, cigarette smoking habits, and family history; I represents the additional contribution of the interaction of variables in $V$ with other variables in $V$ and with chronological age; and $\Delta$ represents the additional contribution of past changes in any of the variables in $V$, and also of changes in variables that are not in $V$ but are important because a change in them implies an elevation or reduction of $y$. The variables in the sets $V$ and $\Delta$ and all constants entering into this function have to be determined from a study of a reasonably large number of individuals followed longitudinally.

## III. A COMPUTERIZED UNDERWRITING EXPERIMENT

Mutual Life of Canada graciously granted the authors the opportunity to test the biological age model by attempting to computerize its underwriting process.

Mutual Life presently issues about 80,000 individual life insurance policies a year. Approximately 75 percent of these policies are issued nonmedically. Even for these policies, the cost of underwriting and issue
averages close to $\$ 100$ an application and the time needed for underwriting averages around five days.

Mutual Life provided coded data on its adult nonmedical applications, including the following information:

1. Beneficiary relationship;
2. Insurance amount;
3. The underwriter's decision (issue standard, issue rated, or decline); and
4. If the decision was other than standard, other information that was requested by the underwriter.

It also provided the answers given to the nonmedical application form as shown in Exhibit 1.

The most serious problem was that there was little or no matching between the nonmedical questions asked by Mutual Life and the questions used in the currently available biological age models. Hence, it was impossible to enter the Mutual Life data into any of the prepackaged biological age models.

Instead, it was decided to access two sets of underwriting data. Each set would consist of approximately eight hundred applications. The first set of applications would be used to build a model that could discriminate between those applicants who were rated or rejected and those applicants who were issued standard without further information. The model developed from this first set of applications then would be used with the second set of applications to see if the model could discriminate correctly between those applicants who safely could be issued insurance at standard rates with no further underwriting and those who could not.

The first group of applications was used to build a model of the type described earlier, where, in this instance, $P\left(x_{1}, \ldots, x_{k}\right)$ is the probability that an individual with variables $x_{1}, \ldots, x_{k}$, corresponding to information from the application, will be judged substandard or rejected. Then

$$
P\left(x_{1}, \ldots, x_{k}\right)=\left[1+\exp \left(-\alpha-\sum_{i=1}^{k} \beta_{i} x_{i}\right)\right]^{-1}
$$

where ( $x_{1}, \ldots, x_{k}$ ) represents responses to a set of $k$ items chosen from the questionnaire, and the $\beta$ 's represent the weights attached to the items.
The model was built from the data on 824 applications, representing approximately one month's adult nonmedical receipts. Ten of these applications were issued on a substandard basis and seventeen were rejected. For the purposes of these analyses, these twenty-seven policies

## EXHIBIT 1

The Mutual Lite Assurance Company of Canada / Waterico. Ontario
To de used only it the lite insured tias arained 16 years of age ! 18 years $n$
APPLICATION PART 2 - EVIDENCE OF INSURABILITY





 buinna

| Eignod m | Dale |
| :---: | :---: |
| Whareas | Sipnoture of LHe intured |

319.81

## EXHIBIT 1-Continued

COMPLETE THIS SECTION FOR PARAMEDICAL AND MEDICAL EXANINATIONS


ADDITIONAL REPORT BY MEDICAL EXAMINEA


## ADDITIONAL REMARKS

sequed at

## strmotere of Eraminer

were grouped into one category, called the nonstandard group. Further, the analysis emphasized only the health-related information from the questionnaire.

Initially, simple summaries comparing the responses of the standard group and the nonstandard group to each of the medical-based questions from the application were prepared. These analyses indicated certain questions for which the response pattern was different in the two groups. Second, as an overall measure of the status of the applicant, a single variable, the number of "no" answers to certain questions, was created. Finally, guided by the results of these preliminary analyses, the model screening program (SMOD; see the earlier description) was used to identify subsets of the questions that would separate the two groups almost as well as the large number of original questions. This latter procedure had to be carried out in steps. At each stage, different combinations of items from the questionnaire were entered into a full model and those items which did not appear to make any significant contribution to the prediction of the nonstandard cases were deleted.

This process finally produced two models that seemed to be able to discriminate between standard and nonstandard lives nearly as well as the full set of independent variables. The variables in these models were the following (the question numbers refer to Exhibit 1):

| Model: | Model 2 |
| :--- | :--- |
| Response to question 8A | Alcohol use |
| Response to question 9B | Cigarette smoking |
| The number of "no" answers | Response to question 8A |
| Age | The number of "no" answers |
|  | Age |

While the models seemed to predict equally well, there were some anomalies in that responding "yes" to question 8 A and to the questions on alcohol use and cigarette smoking increased the estimated probability of being judged standard. (Those patterns also were apparent in the original data: a higher proportion of standard lives drank, and a higher proportion smoked.)

With the maximum likelihood estimates of the coefficients in the model, it was possible to estimate, for each subject, his or her chance of being judged standard. By assigning a standard classification to any applicant with an estimated probability of being standard in excess of a chosen cutoff level, it was possible to assign each applicant to one of the four cells in the summary table below (Table 3).

TABLE 3
Results of Classification Based on the Model

| Modfl <br> Ci.assification | actual Rating |  |  |
| :---: | :---: | :---: | :---: |
|  | Standard | Nonstandard | Total |
| Standard | $n_{00}$ | $n_{01}$ | . |
| Nonstandard. | $n_{10}$ | $n_{11}$ |  |
| Total. | 797 | 27 | 824 |

Thus, in the table, $n_{00}+n_{11}$ cases are correctly classified, while $n_{10}+$ $n_{01}$ are incorrectly classified. By varying the cutoff level it is possible to increase or decrease the number predicted to fall in the standard class. For the purposes of this illustration, the cutoff level 797/824 $=0.9672$ was chosen, as this produced small values of $n_{01}$ with reasonably small values of $n_{10}$. In practice, one could choose a cutoff level that reduced the size of $n_{01}$ at the expense of increasing $n_{10}$ by assessing the costs of misclassifying a standard as a nonstandard against the costs of the other misclassification (that is, the extra cost of underwriting standard cases balanced against missing a nonstandard case). Alternatively, full traditional underwriting could be required for a chosen percentage of cases with the lowest estimated probabilities of being standard.

When applied to the original data set, using the cutoff level 0.9672 , the two models were able to discriminate as shown in Table 4.

Thus, using Model 1 , only 15.9 percent ( $131 / 824$ ) of the cases were misclassified, but, most importantly, only 2 nonstandard cases were misclassified as standard. Increasing the cutoff to 0.975 resulted in only 1 nonstandard case being misclassified as standard, but 151 standard cases were classified as nonstandard. This one nonstandard case could not be correctly classified with a cutoff level as high as 0.99 . (Further investigation revealed that this case was rated nonstandard on the basis of special

TABLE 4
Results of Classification for Models 1 and 2

| Model <br> Classification | actual Rating |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Model 1 |  |  | Model 2 |  |  |
|  | Standard | Nonstandard | Total | Standard | Nonstandard | Total |
| Standard | 668 | 2 | 670 | 681 | 4 | 685 |
| Nonstandard | 129 | 25 | 154 | 116 | 23 | 139 |
| Total | 797 | 27 | 824 | 797 | 27 | 824 |

TABLE 5
Results of Classifications Based on Models 1 and 2 for the Second Data Set

| Model Classification | actual rating |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Model 1 |  |  | Model 2 |  |  |
|  | Standard | Nonstandard | Total | Standard | Nonstandard | Total |
| Standard | 680 | 0 | 680 | 684 | 0 | 684 |
| Nonstandard | 139 | 10 | 149 | 135 | 10 | 145 |
| Total | 819 | 10 | 829 | 819 | 10 | 829 |

information on the applicant's arthritis, gout, and rheumatism obtained from X-ray examination.) Model 2 did not fare quite so well, misclassifying fewer cases overall, but missing 4 out of 27 nonstandard cases ( 3 out of 27 using a level of 0.975 ).

It is well known that regression models often predict considerably better for the data set on which they were built than for other similar data sets; but in testing these models on the next 829 applications coded, as indicated in Table 5, both models were able to identify correctly all 10 nonstandard cases! Model 1, using a cutoff point of 0.9672 , misclassified 139 standard cases as nonstandard, while Model 2, with the same cutoff level, did marginally better, misclassifying 135 standard cases.

Thus, Model 1 would have declared 680 applications as standard, leaving only 149 ( 18 percent) to be underwritten in the usual way. This could have resulted in significant savings in the cost of underwriting, balanced against an additional expense of approximately $\$ 0.62$, the cost of computer time to use the model to classify the 829 applications.

As pointed out earlier, Mutual Life issues nearly 80,000 individual life insurance policies a year. Seventy-five percent of these are issued nonmedically, with an underwriting and issue cost of around $\$ 100$ each and processing time of close to five days. Only 3.5 percent of the nonmedical applications are rated or declined, on average.

## iv. CONCLUSION

Considerable work remains to be done in building a suitable discrimination model. However, it has been shown, through the use of a fairly crude model, that a computer program can produce results very close to those determined by human underwriters. This was done using input data not designed for computerization or based on any preconceived model such as the biological age model.

A great deal of the underwriting that is being done in an expensive and relatively slow manner today could be computerized. This would require
using a machine-readable application form with input more suited to the existing biological age models, although the latter may not be essential.

One of the exciting prospects of a computerized underwriting model is that it can reassess itself continuously. For example, every time a policyholder dies, the computer can retrieve the application form for the policyholder and determine what information was provided that might have predicted that early (normal, or late) death. In this manner, the computer can statistically reanalyze the weights that have been given to each input parameter and improve its own program continuously.

With this computerized model, a much more refined pricing stratification than exists today is possible. No longer will 75-85 percent of all cases be priced according to sex and chronological age only. Rather, the computer will determine the time to death in its program and set the proper premium level accordingly.

This same methodology, applied to life annuities, would be responsive to the feminists clamoring for unisex annuity mortality tables, since companies no longer would be pricing on the basis of sex and chronological age only. Rather, they would be using an objective statistical prediction as to time to death.

One can visualize a day, in the not-too-distant future, when an agent will enter the client's home with his portable computer terminal. After using the terminal as a sales aid (to show cost comparisons and investment attributes) the agent will ask the client the usual application questions. The answers to these questions will be entered into the computer through the portable terminal and, in a matter of seconds, the computer will tell the agent whether his client has been accepted or rejected, or whether further information is required. (The term "rated" no longer will be used.)

If the client is accepted, the computer will calculate the price level for the coverage requested based on the statistical analysis of time to death. Then, if the client is in agreement, the portable terminal will print out a policy and the process will be complete!

## V. ACKNOWLEDGMENTS

The authors would like to thank the Mutual Life of Canada and, in particular, Barry J. Triller (new business executive) and Wilhelmina Gould (new business analyst) for their assistance with this project. Without their help, this research could not have been completed. We also would like to acknowledge the assistance of Evan Kelly, who was responsible for the computer analysis.

## APPENDIX

HEALTH HAZARD APPRAISAL
Risk Factors: Detail and Codes

| Factor | Abbreviation | Code | Description |
| :---: | :---: | :---: | :---: |
| Sex | SEX | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Male Female |
| Age | AGE |  | Enter age in years. |
| Alcohol habits | ALCOHOL | $\begin{aligned} & 1 \\ & 2 \\ & 3 \\ & 4 \\ & 5 \\ & 6 \end{aligned}$ $7$ | 41 or more drinks per week* <br> 25-40 drinks per week <br> 7-24 drinks per week <br> 3-6 drinks per week <br> 1-2 drinks per week <br> Stopped: stopped drinking (person has stopped before symptoms of cirrhosis). <br> Factor should be given to stopped drinkers regardless of amount. <br> Nondrinker: Never been a drinker |
| Arrest record | ARREST RECORD | $\begin{aligned} & 1 \\ & 2 \\ & 3 \end{aligned}$ | Burglary, robbery, assault Without violence or threat No arrests |
| Weapons | WEAPONS | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Carries <br> Does not carry |
| Depression | DEPRESSION | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Often severely depressed Seldom or never severely depressed |
| Miles per year | MItes |  | Enter miles driven per year and/or miles as an auto passenger. |
| Seat belt use | SEAT BELT | 1 2 3 4 | Worn less than $10 \%$ of the time Worn $10-24 \%$ of the time Worn $25-74 \%$ of the time Worn $75-100 \%$ of the time |
| History of bacterial pneumonia | PNEUMONIA | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Has had <br> Has not had |
| Blood pressure, systolic (if unsure enter 120) | BP: SYSTOLIC |  | Enter systolic blood pressure in mm. |
| Blood pressure, diastolic (if unsure enter 80) | BP: DIASTOLIC |  | Enter diastolic blood pressure in mrr. |
| Blood cholesterol (if unsure use 2) | CHOLESTEROL | $\begin{aligned} & 1 \\ & 2 \\ & 3 \end{aligned}$ | Cholesterol level 280+ <br> Cholesterol level 220-279 <br> Cholesterol level 219 and below |
| Diabetes | DIABETES | $\begin{aligned} & 1 \\ & 2 \\ & 3 \end{aligned}$ | Diabetic Diabetic (controlled) Not diabetic |
| Height | HEIGHT |  | Enter height in inches with shoes (without shoes: add 1 inch for males, 2 inches for females). |
| Weight | WEIGHT |  | Enter weight in pounds (in indoor clothing and shoes). |

[^3]APPENDIX-Continued

| Factor | Abbreviation | Code | Description |
| :---: | :---: | :---: | :---: |
| Frame | FRAME | 1 2 3 | Small Medium Large |
| Drugs and medication influencing motor vehicle operation | DRUGS/MED | 1 2 3 | Excess <br> Moderate <br> None |
| Exercise | EXERCISE | 1 | Sedentary: work and leisure; under 5 flights of stairs or half-mile walking per day |
|  |  | 2 | Low moderate: some activity, work and leisure; between 5 and 15 flights of stairs or 0.5 to 1.5 miles walking or comparable daily activity <br> High moderate: programmed exercise 4 times per week or 1.5 to 2 miles of walking or 15 to 20 flights of stairs or comparable daily activity <br> Vigorous: greater than moderate |
|  |  | 34 |  |
|  |  |  |  |
| Smoking habits: <br> (1) for current smoker, heaviest amount smoked in past 5 years; (2) for exsmoker, heaviest amount smoked in year before quitting | SMOKING | 1 | Cigarettes, 40 or more/day Cigarettes, 20-39/day |
|  |  | 3 | Cigarettes, 10-19/day |
|  |  | 4 | Cigarettes, less than 10/day |
|  |  | 5 | Cigars or pipes only; 5 or more/day or any amount inhaled |
|  |  | 6 | Cigars or pipes only; less than 5/day not inhaled |
|  |  | 7 | Nonsmoker (never smoked or not smoked for 10 years) |
| Current smoking status | STOPSMOK | 0 | Still smoking or nonsmoker <br> Years of having stopped smoking |
|  |  | 1 |  |
|  |  | 3 |  |
|  |  | 4 5 |  |
|  |  | 6 |  |
|  |  | 7 |  |
|  |  | 9 |  |
| Family history of ischemic heart disease | FH/HEART | $\cdots$ | Both parents died before 60 of ischemic heart disease. <br> One parent died before 60 of ischemic heart disease. <br> One or both parents died before 60 of cause other than ischemic heart disease or both are still alive and below age 60. <br> None of the above |
|  |  | 2 |  |
|  |  | 3 4 |  |
| Family history of diabetes (mother, father, sister, brother, child) | FH/DIAE | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Yes No |
| Farnily history of suicide | FH/SUICD | 1 | Yes <br> No |
| Emphysema and/or bronchitis | EMPHYSEMA | 1 | Has emphysema and/or bronchitis Has no signs or symptoms of emphysema and/or bronchitis |

APPENDIX-Continued

| Factor | Abbreviation | Code | Description |
| :---: | :---: | :---: | :---: |
| Rectal polyp | POL.YP | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Has had Has not had |
| Proctosigmoidoscopy | Procto | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | Has annually Does not have annually |
| Rectal bleeding | RCTBLOOD | 1 | Has had undiagnosed rectal bleeding in the past year <br> Has not had undiagnosed rectal bleeding in the past year |
| Chronic rheumatic heart disease | RH: FEVER | 1 2 3 4 5 | Rheumatic heart murmur, no chemoprophylaxis <br> Rheumatic heart murmur, on chemoprophylaxis <br> History of rheumatic fever but no murmur, no chemoprophylaxis <br> History of rheumatic fever but no heart murmur, on chemoprophylaxis <br> No history of rheumatic fever and no rheumatic heart murmur |
| Signs or symptoms of chronic rheumatic heart disease | RH: $\mathbf{S / O} / \mathbf{S}$ | $\begin{aligned} & 1 \\ & 2 \end{aligned}$ | No Yes |
| Ulcerative colitis | ULCERCOL | $\begin{aligned} & 1 \\ & 2 \\ & 3 \end{aligned}$ | Has had ulcerative colitis 10 years or more <br> Has had ulcerative colitis less than 10 years <br> Has no symptoms of ulcerative colitis |

The following factors are to be coded for females only:

| Vaginal bleeding | Vagblood | 1 2 | Has had undiagnosed vaginal bleeding in past year <br> Has not had undiagnosed vaginal bleeding in past year |
| :---: | :---: | :---: | :---: |
| Age at marriage or onset of intercourse | AGE/MAR | 1 2 3 | Teenage $20-25$ <br> Over 25 or never |
| Pap smear | PAPSMEAR | 1 2 3 4 | Has not had <br> Negative within 5 years <br> Negative within 1 year 3 negative within 5 years |
| Economic and social status | SOCIO/EC | 1 2 3 | Low <br> Average High |
| Jewish | JEWISH | 1 2 | No Yes |
| Family history of breast cancer | F-M/BREAST | 1 2 3 4 | Mother or sister had breast cancer. <br> Mother or sister had breast cancer but patient examines breasts regularly and has periodic examination by physician <br> Neither mother nor sister had breast cancer. <br> Neither had breast cancer but patient examines breasts regularly and has periodic examination by physician. |

## REFERENCES

1. Borkan, G. A. "Assessment of Biological Age Using a Profile of Physical Parameters," Journal of Gerontology, XXXV, No. 2 (1980), 177-84.
2. Brown, K. S. "Mathematical Contributions to the Study of Risk Factors in Cardiovascular Disease. II," Math Scientist, II (1977), 111-25.
3. Brown, K. S., and Forbes, W. F. "Concerning the Estimation of Biological Age," Journal of Gerontology, XXII (1976), 428-37.
4. Brown, K. S., and Nabert, W. "Evaluation of the Existing Method for Calculating Health Hazard Appraisal Age." Unpublished report for the Nonmedical Use of Drugs Directorate, Health Protection Branch, Health and Welfare 1, Canada, 1977.
5. Comfort, Alex. The Biology of Senescence. New York: Churchill Livingstone, 1956.
6. -_Test-Battery to Measure Aging-Rate in Man," Lancet, VI (1969), 1411-14.
7. Cornfield, J. 'Joint Dependence of Risk of Coronary Heart Disease on Serum Cholesterol and Systolic Blood Pressure: A Discriminant Function Analysis," Federation Proceedings, American Society for Experimental Biology, XXI, No. 4: Part II, Suppl. II (1962), 58-61.
8. Hershey, Daniel. A New Age-Scale for Humans. Lexington, Mass.: Lexington Books, 1980.
9. Hocking, R. R. "The Analysis and Selection of Variables in Linear Regression,'" Biometrics, XXXII (1976), 1-50.
10. Lawless, J. F., and Singhal, K. "Efficient Screening of Nonnormal Regression Models," Biometrics, XXXIX (1978), 318-27.
11. Palmore, E., and Jeffers, F. C. Prediction of Life Span. Lexington, Mass.: Health Lexington Books, 1971.
12. Rao, C. R. Linear Statistical Inference and Its Applications. New York: Wiley, 1968.
13. Robbins. L., and Hall. J. R. How to Practice Prospective Medicine. Washington, D.C.: U.S. Public Health Service, 1970.
14. Rockstein, M. Theoretical Aspects of Aging. New York: Academic Press, 1974.
15. Ross, C. L. Predicting Longevity. Lexington, Mass.: Heath Lexington Books, 1971. 1971.

# DISCUSSION OF PRECEDING PAPER 

## STEVEN HABERMAN:

The paper introduces some of the recent developments in statistical methodology that are applicable to life insurance underwriting.

Discriminant analysis is used to develop an automatic procedure for identifying those applications that are most likely to be accepted on a substandard basis or rejected. The concept of biological age is introduced but not fully developed. Thus, Table 2 in the paper assigns biological ages on the basis of serum cholesterol, systolic blood pressure, smoking status, and the comparative risk of developing cardiovascular disease relative to an average person. The concept of biological age is most useful in life assurance underwriting when the endpoint under consideration is death rather than the development of a particular disease.

The authors have not discussed models for assessing the absolute and relative survivorship (and hence mortality) of standard and substandard lives. It is here that considerable advances in methodology have appeared in the statistical literature, extending the multiple decrement table [1-3]. It is now possible to relate survival to a set of covariates measured at the time of an individual's application, through an adaptation of regression [1-2]. This sort of technique would lead to the identification of factors or sets of factors that significantly shorten or lengthen survival for standard and substandard lives. Hence, an individual's profile could be transformed into a measure of biological age as the authors suggest in their paper.

## REFERENCES

1. Cox D.R. "Regression Models and Life Tables" (with discussion). Journal, Royal Statistical Society, XXXIV (1972), 187-220.
2. Kalbleisch J.D. and Prentice R.L. The Statistical Analysis of Failure Time Data. J. Wiley, New York, 1980.
3. Haberman S. "Mortality Studies: Measurement of Experience and Comparison with Expected.' Journal, Institute of Actuaries, CIX (1982), 203-23.

## JOHN WEST HADLEY:

I was fascinated by the authors' attempts to reproduce human underwriting via the computer. This idea has had great appeal for me, although my concept essentially had been to program the medical underwriting manual and similar
decision procedures regarding aviation, avocations, and other insurance in force and so forth. All information on the application would be keyed into the computer, which would indicate the appropriate underwriting action. Naturally a great many applications would involve either gray areas for which the manual provides no clear cut action (such as relatively new medical techniques), or combinations of various conditions too complex to program effectively. In such situations, the computer simply would reject the case as one requiring evaluation by an underwriter. In this way the computer could handle the simpler cases, freeing the underwriter for the more difficult ones. This also would ensure more consistent underwriting, and possibly increase the underwriter's job satisfaction by reducing the "rubber stamping" content of his work. Underwriters could spend more time researching new developments in medicine to refine the underwriting process. Computer underwriting could be used to experiment with various underwriting guidelines without confusing those doing the underwriting. The computer also could serve as a training tool by providing a quick check on how well the underwriter is doing.

I would like to know if the authors examined the approach I've described and whether or not they consider it feasible. Admittedly, the initial job of establishing the program would be mammoth, but even that would not be without its benefits. Almost certainly, it would generate a great deal of consideration of the manner in which various conditions interrelate and how best to treat them in the underwriting process.

Advances in medicine provide a possible pitfall in the practical application of the model. The user would need to monitor changing underwriting practices carefully and test the validity of the model periodically. Not just the weightings but also the variables entering the model likely would change over time. Factoring experience back into the model will help, but it also is important to reflect factors not previously available or without previous significant impact, but considered likely to affect future experience.

I suspect most insurers will be very slow to accept this model as a viable alternative, despite the demonstrable cost savings. I would be interested to know how it was accepted at Mutual Life Assurance, particularly by the underwriters, and how extensively they have used it since this work.

How effectively might the procedure be applied to individual health insurance, either disability income or major medical? One problem is that the percentage of policies not issued as applied for (including declinations, rated issues, and standard issues with exclusion riders) is much greater than for life insurance. If the computer were used only to provide definite issue
decisions, with the underwriters reviewing the rest, how long might it take to recover the initial investment?

I believe there was a minor flaw in the cost justification. The cases rated standard by the computer likely are the easier ones to underwrite, and those generating fewer medical requirements, so that the average cost to underwrite the remaining cases should be larger than the overall average. This increase in unit cost, plus the relatively insignificant computer cost, times the number of cases "humanly" underwritten, should be deducted from the cost savings on the computer-underwritten cases.

I thank the authors for an enlightening paper.

## (AUTHORS' REVIEW OF DISCUSSION)

ROBERT L. BROWN AND K.S. BROWN:
We thank Mr. Hadley and Dr. Haberman for their thoughtful comments on our paper. As indicated in the paper, our original interest was to investigate whether existing "biological age" models could be used in the underwriting process. Unfortunately, there was little correspondence between the variables input to these biological age models and those appearing on the application form. Thus, we adopted the approach outlined in the paper. We agree that programming the underwriting manual would be a mammoth task, and we initially did not consider that approach for that reason. Our aim was to determine whether we could duplicate the ratings of underwriters using this simpler model, which does isolate those variables that seem to be important in underwriting the given set of applications. To this end we were reasonably successful.

Advances in medicine pose problems to any model that seeks to predict future claims, including a standard approach to underwriting. We agree that any model would need to be monitored closely, and would argue that this is one advantage of computerizing the entire process; namely that claims information can be combined with information obtained from the application to update and refine the model continually.

Dr. Haberman refers to recent advances in statistical methodology that permit survival to be related to a set of covariates. We are extremely interested in applications of this methodology but lack the raw data on which to investigate the potential applications to the underwriting process. Again, a computerized system would enable the data to be collected routinely.

Mr. Hadley's comments concerning cost comparisons are well taken. However, the computer still can serve as a useful screening device, underwriting the straightforward cases, and possibly routing the more complicated
cases to the underwriter best able to do the underwriting of the application. Further, in the case of the Mutual Life data, approximately 10 percent of the applications were absolutely clear (no "yes" answers). Obviously there should be no need for human underwriting of these applications.

Mr. Hadley mentions one useful spinoff advantage of having a computerized underwriting system, namely, being able to use it to train new underwriters. It also can be used to check the consistency of the present underwriters by giving them the same applicant profile and determining if they all make the same decision every time.

Mr. Hadley asks how the new system was accepted at Mutual Life. To date, our ideas have not been adopted at Mutual Life. We understand that this project has relatively high priority but the systems people are occupied with other problems at the moment. Nevertheless, we do not foresee widespread adoption of the methodology, although we feel it is sound and has obvious cost-saving potential.

Finally, we cannot offer any comments on the applicability of our ideas to health insurance since we are not experts in this area. We feel that morbidity would be much more difficult to handle than mortality.

Again, sincere thanks to the two discussants for their stimulating remarks.


[^0]:    * Dr. Brown, not a member of the Society. is associate professor of statistics and actuarial science at the University of Waterloo.

[^1]:    ${ }^{1}$ For example, T. Gordon and W. B. Kannel, "The Framingham Massachusetts Study: Twenty Years Later." In I. I. Kessler and M. L. Levin (eds.), The Community as an Epidemiological Laboratory: A Casebook of Community Studies, pp. 123-46. (Baltimore: Johns Hopkins University Press, 1970).

[^2]:    ${ }^{2}$ Note: the prime (') in these equations denotes the transpose of the matrix.

[^3]:    * Number of "drinks" should include aperitifs, wines, beer, etc.

