Utilization of Health Services as Events: An Exploratory Study

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The concept of propensity to use ambulatory care is defined as the probability that a utilization occurs in a very small interval of time, given that no utilization has been observed before. With this definition of utilization, survival analysis can be used to assess the effect of a set of predictors on utilization. The results of this analysis are compared with the results of the prediction of utilization by the same set using a logistic regression model and a linear regression model.

Recent studies on utilization of health care services have measured this variable using the volume of utilization over a period of time, or using a dichotomous variable distinguishing individuals with at least one utilization from those with no utilization over a period of time. However, a number of other studies have suggested, on theoretical or empirical grounds, that these indicators are inappropriate. For example, Wolinsky and Coe (1984) obtained different results with a regression model predicting utilization when either the volume of utilization, the log of the number of visits to physicians, or the distribution of the number of visits (truncated at 13 visits per year) was used as the dependent variable. These authors concluded that the last two indicators were superior to the first because they were explaining more variance; they also suggested that a model of utilization should pertain to low and medium levels of utilization on the one hand, and to high

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levels on the other. Other studies have shown that visits to the physician were followed by other, related visits. Brown et al. (1971) found that for 26.7 percent of the visits, the physician was asking for a follow-up, and that 56 percent of the workload of a physician consisted of follow-up visits. The Cornell et al. (1980) study found an even higher level of prescribed follow-up visits.

On the theoretical level, Gold and Azenedo (1982) have suggested that patients do not seek "care" when visiting a physician, but rather the "solution to a problem." As a consequence, the patient may demand more than one visit—to be sure the problem has been, or is being, considered. Hornbrook et al. (1985) proposed that episode of "disease" and episode of "illness" should be distinguished from episode of "care." A conclusion to be drawn from this distinction among the three types of episodes is that a study of utilization of health care services should choose any of them, although Hornbrook and Berki (1985) argue for considering only the episode of illness in utilization study.

Hulka and Wheat (1985) have deplored the gap between the conceptualization of utilization and the measures used in utilization study. This gap is a major problem in the social sciences in general (Blalock, 1968; Blalock, 1982). Harel et al. (1985) have stated a more general and important criticism about utilization studies: that they lack theoretical foundation altogether. One indication of this is that different indicators of utilization are used without any effort to define their specific meaning. One exception to this trend is the distinction Hershey et al. (1975) made between utilization per se, measured by the volume of care in a given period, and the fact that utilizing or abstaining from utilizing in a given period can be defined as an indicator of access to care. Although this definition of access would not make unanimity (for example, see Thomas and Penchansky, 1984), the advantages in the Hershey et al. approach lie in the attribution, to two different indicators, of a substantive meaning that can be construed in theoretical terms. Among other things, Hershey et al. imply that the fact of using a health care service in a period of time is the successful actualization of a propensity to use it that characterizes the patient rather than the system.

In this article, the concept of propensity will be defined in operational terms and related to a specific measure of utilization that stems from Hershey et al.'s preoccupations. In addition, data on ambulatory care utilization by a sample of urban Canadians will be used to illustrate concretely the following conceptual development.

PROPENSITY TO USE HEALTH CARE SERVICES

In defining his model of health care utilization, Andersen and colleagues (1975, 1980, 1973) used the concept of propensity. This term defines the predisposing variables included in the model. The Andersen model explains observed utilization by propensity to use. In this article, the links between utilization and propensity will be defined before independent variables are brought into the model.

Let us assume a process that consists of a transition from no utilization to utilization of health services. For simplicity, let us assume further that transition rates are constant over time and homogeneous in the population. If p is the probability of no utilization, $1 - p$ the probability of utilization, and q the transition rates from no utilization to utilization, then the transition to utilization at time t is described (by Coleman, 1981):

$$\frac{dp}{dt} = -qp \qquad (1)$$

The transition rates from no utilization to utilization within a period of time t can be defined as the probability that a utilization will occur in a very small interval of time Δt, given that the individual has not used health services before that period of time. This is the definition of the propensity to use health care services that we propose here. It is also the instantaneous probability of using such a service, given that no utilization occurred before.

If the probability of no utilization depends on the transition rates and on the utilization status at a preceding period ($t = 0$, say), then integrating Equation 1 gives:

$$p(t) = p(0)\, e^{-qt} \qquad (2)$$

An estimate of $p(t)$ can be obtained by knowing the proportion of individuals that had a utilization in the period t, given that the individuals had had no utilization at the beginning of the period ($t = 0$). Note that this information is usually collected in utilization study and that knowing that an individual has not utilized a health service in a period of time is not the same as knowing that an individual is not using one at the moment of the data collection. Thus, utilization studies usually have much more information at their disposal than standard cross-sectional studies, although they rarely make use of this supplemental information. To use a metaphor, utilization studies provide an estimate of the proportion of survivors (nonusers) within a period of time. Those who did not use a health service in a period are those who survived, while the length of the period of survival is not known for them (these cases are right-censored).

The information available in most surveys on utilization can be used to estimate the transition rates in Equation 2, given that $p(0) = 1$. Inasmuch as the level of utilization is unknown at $t = 0$, then at least two observations are required to estimate the transition rate. Knowledge of an individual's state at t_0 is pertinent for utilization of hospital services, because hospital stay includes measurable periods of time. As a consequence, equations 1 and 2 should be modified to include a second transition rate: the transition from hospital to the community. It is thus possible that an individual had been hospitalized before t_0 and remained in the hospital after t_0. In the case of ambulatory care utilization, the knowledge of an individual's state at t_0 is less important inasmuch as a visit to a physician is an almost instantaneous event over a six-month or one-year period. But if the utilization of ambulatory care is studied in the context of the study of episode of care, one must know the state in which an individual finds himself (within or not within an episode of care) at the beginning of the period.

A simple model for utilization of ambulatory care would be:

$$p(t) = e^{-qt} \tag{3}$$

If transition rates depend linearly on a set of predictors x_j, the equation becomes:

$$p_i(t) = \exp(-t \sum_j \beta_j x_{ji}) \tag{4}$$

Thus, for individual i, the log of the probability to use (a medical service) is linearly related to a set of predictors.

The difference between the model defined in Equation 4 and the usual regression models of utilization is that the transition rates rather than the probabilities to use are explained by a set of factors. The functional form of the relation between the probabilities to use and the predictors depends on the functional form of the relation between (1) the probabilities to use and the transition rates, and (2) the transition rates and the predictors. In most of the models currently found in the literature, the predictors are directly and linearly related to the probabilities to use a medical service.

Now, when only one kind of event is possible in a period of time, the transition rates are equal to hazard rates, a concept useful in survival data analysis (Tuman and Hannan, 1984). This suggests that the propensity to use health care services can be defined as a hazard rate. It also suggests that knowledge of the date at which a utilization occurs might yield results that are quite different from the one obtained from linear regression analysis. Also, nonparametric methods of estimating hazard rates and the coefficients in a predictive model (Lee, 1980) are available. As a consequence, the constraints imposed on model 2 can be removed (Hershey, Luft, and Giandris, 1975).

One of the models for predicting hazard rates from a set of predictors is the Cox model (1984) described by:

$$ln \frac{h_i(t)}{h_0(t)} = \sum_j \beta_j x_{ji} \tag{5}$$

where

$h_i(t)$ = the hazard rates for individual i.
$h_0(t)$ = the hazard rates with all of the β_j equal to zero.
x_{ji} = the values of the predictors j for individual i.
β_j = the effect coefficients.

This equation assumes that the sequence of the ordering of the first visit of a sample of individuals within a period of time t ($t = 0, \ldots, T$) is known.

In what follows, a comparison of the results of utilization prediction will be made with seven independent variables, using three models. The three models are the Cox regression model for survival data, the logistic model, and the linear regression model. The statistical significance of the effect of these variables in each of the models will be obtained and the results of the stepwise regression analysis compared.

EMPIRICAL ANALYSIS

DATA AND METHODS

The data used in this analysis come from a set of individuals living in the metropolitan area of Québec and in the city of Laval, which is located in the Montréal metropolitan area. These two areas are well provided with health care resources. This set of individuals was drawn from the 1981 physician claims file of the *Régie de l'assurance-maladie du Québec (RAMQ),* the agency responsible for the administration of the Quebec Health Insurance Plan. The physician claims in 1981, 1982, and 1983 for these individuals are recorded on the file. To provide a set of cases without left-censoring, only individuals without utilization of ambulatory medical care services and/or hospitalization in 1982 were retained for analysis. Thus, the probability is rather high that the first utilization in 1983 began a new episode of care. This selection procedure produced a set of 11,922 individuals. Because BMDPC programs 1L and 2L provide space for no more than 1,000 cases, a random sample of 980 cases was drawn from the set of 11,922 individuals for this study.

The sample's distribution on some of the variables is unusual because it excludes individuals who had used medical services in 1982. For example, the sample includes only 4.1 percent of individuals 65 years old and over, while these individuals represent 7.2 percent of the total 1983 sample. The proportion of women in the study sample is .372, while their proportion in the whole 1983 sample is .549. Thus, the sample is made up of individuals with characteristics associated with a low rate of utilization. Nonetheless, 11.9 percent of the sampled individuals had six visits or more to a physician in 1981, while 49.1 percent had only one visit. The same year, 27.5 percent of this sample had no visits. The mean number of visits in 1981 was 3.4, a figure much lower than the average five visits for the whole sample.

Using these data, this study compares the behavior of some predictors of utilization using two strategies: (1) a study of the propensity to use health care services with survival data analysis, and (2) a study of access to care measured by the dichotomous dependent variable utilization/no utilization, with (a) a logistic regression model and (b) a linear regression model. In this case, the dependent variable is measured as if the data were collected on the 180th day of 1983, where the question asked of the sampled individuals would be: "Did you visit a physician in the preceding six months?" This cutting point was used because the dependent variable should reflect, though imperfectly, an individual's propensity to use which manifests itself in a variation in the urge to use a medical care service in a period of time. Thus, those who used a medical care service in the first six months of 1983 should have a higher propensity to use such a service than those who did not.

The predictors of utilization are: the sex of the user, the age of the user, the location of the user in either the city of Laval or the Québec metropolitan area, the number of visits in 1981, whether the physician visited was a general practitioner or a specialist, and whether or not the visits occurred in a private office. Most of the visits that did not occur in the private office of a physician were in hospital emergency wards.

The three methods of estimating effect on utilization do not produce a unique comparable statistic, as a R^2, that allows for a comparison of the efficiency of the models. The significance and the direction

Table 1: Results for the Three Models

Independent Variables	*Coefficient*	*Standard Deviation*	t-*Value*
Cox Survival Model			
Age	.0005	.0018	0.3037
Sex	-.0930	.0671	-1.3862
Area	-.0591	.0665	-0.8896
Physician specialty	-.0225	.0808	-0.2785
Private office	-.0459	.0784	-0.5854
Utilization in 1981	.0209	.0023	9.0794
Global X^2 = 114.75; d.f. = 6; p-value = .0000			
Logistic Linear Model			
Age	-.0007	.0044	-0.1734
Sex	-.1106	.0811	-1.363
Area	-.0359	.0789	-0.4549
Physician specialty	.0279	.0988	0.2824
Private office	.0758	.0909	0.8325
Utilization in 1981	.2549	.0401	6.351
Goodness of fit X^2 = 845.48; d.f. = 849; p-value = .528			
Linear Regression Model			
Age	.0000	.0007	0.0137
Sex	-.0464	.0279	-1.6631
Area	-.0020	.0277	-0.0720
Physician specialty	.0166	.0337	0.4917
Private office	.0206	.0326	0.6333
Utilization in 1981	.0059	.0015	3.9079
R^2 = .0199			

of the effect of the independent variables will be used instead of this statistic. It will also be shown that survival data analysis provides tools other than regression methods to explore the data. These descriptive tools can be used to understand to a greater extent the relationship between an independent variable and utilization. They can also provide insight regarding the exact form into which a model predicting utilization can be parametrized.

THREE REGRESSION METHODS

Table 1 gives the results of the three regression procedures. Clearly, only one variable has any effect on the propensity to use ambulatory care: the level of utilization in 1981. This result is in line with other studies (Evashwick et al., 1984; McCall and Wai, 1983; Thackher et al., 1978) that have shown past utilization as a good predictor of contemporary utilization. But the percentage of variance explained by this variable is small in the linear regression model. Although each of the three models yields the same global result, the standard deviations are much smaller in the Cox survival model than in other models, given the estimate of the coefficients. Thus, the estimate of the effect in the Cox survival model is more precise.

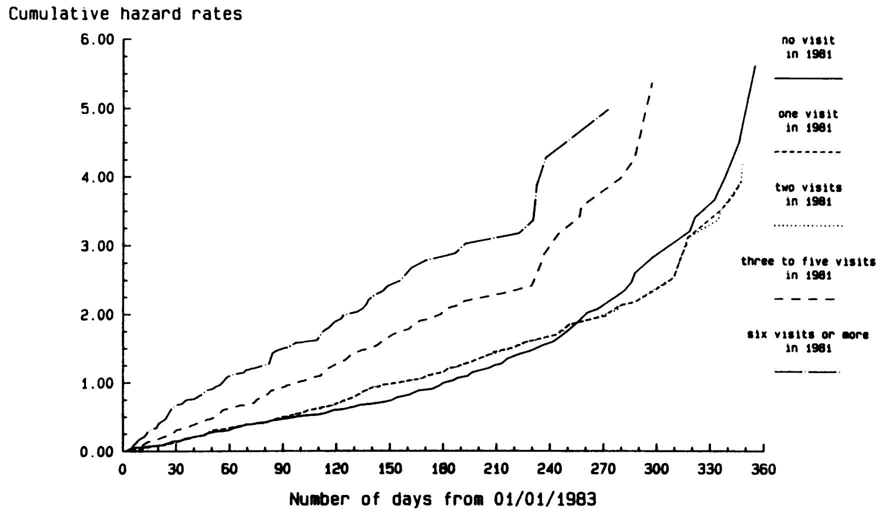
In this analysis, the variables excluded from the equations on the basis of a statistical test were the same in the three models. But there is some evidence that the Cox survival model is more acceptable, because the estimates have a smaller confidence interval (and thus are more precise) than the logistic and linear regression models. There are reasons to believe that a study using well-chosen variables can reach different results with the richer Cox survival model than with any of the other two models.

A GRAPHIC ANALYSIS OF PROPENSITY TO USE AMBULATORY CARE

A study of the hazard rates involves more than coefficients in a Cox regression model. The examination of the plots of the cumulative hazard rates for ranges of values of the effect variable yields information (1) on whether the differences in the hazard rates between ranges of values appear over the whole distribution or are located within specific values and (2) on whether the form of the distributions of the cumulative hazard rates is the same for each of the ranges of values of the effect variables. Thus, a study of the utilization of health care services using survival data analysis can go beyond the reading of a R^2 statistic to estimate the effect of a variable or a set of variables on utilization. On the one hand, a statistic such as a R^2 can be misleading in identifying the weight of a variable in explaining utilization. A variable can have a very important effect on a limited set of values of hazard rates. On the other hand, the form of the distribution of hazard rates is significant in its own right: an exponential distribution of time until utilization implies that utilization is not time dependent, while other distributions (the Weibull distribution, for example) imply that the intensity of the propensity to use medical care varies with time. If cumulative hazard rates are plotted for different ranges of values of an effect variable, the form of their distribution can be studied and different kinds of distributions identified.

To illustrate these two points, the cumulative hazard rates have

Figure 1: Propensity to Use Ambulatory Care, by Number of Previous Visits (Cities of Laval and Metropolitan Area of Québec, 1983)



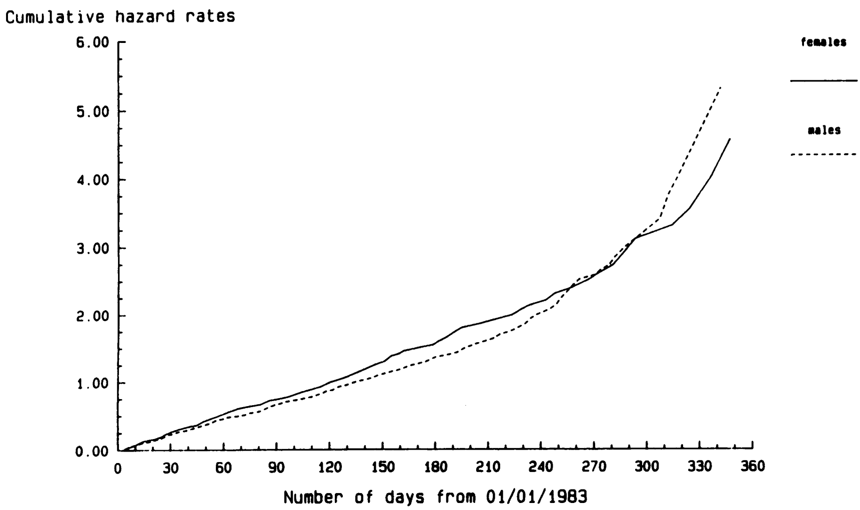
Note: The hazard rates curves for one and two visits are almost the same.

been plotted in Figure 1, for different utilization levels in 1981, and in Figure 2, for each of the sexes.

The only potent variable in the three regression models found in Table 1 is utilization levels in 1981. This variable has been categorized into five classes involving (1) 28.0 percent of individuals with no visits in 1981, (2) 20.9 percent of individuals with one visit in 1981, (3) 14.2 percent with two visits, (4) 22.0 percent with three to five visits, and (5) 14.9 percent with six visits or more. Each of these classes has at least 140 individuals, enough cases to proceed with an analysis.

In Figure 1, the cumulative hazard rates are plotted against time. If the plotted cumulative hazard rates curve represents a straight line, it can be deduced that the hazard rates are constant over time. Clearly, only the curve for the six-visits-or-more utilization level in 1981 can pretend to approximate a straight line. The curves for the no-visit, one-visit, and two-visit levels show that as time passes, the propensity of individuals to use health care increases. Also, the curve for individuals with six visits or more in 1981 is shorter and steeper than the curves for other levels of 1981 utilization. Thus, individuals with six visits or more in 1981 used health care services in 1983 much earlier than the

Figure 2: Propensity to Use Ambulatory Care, by Sex (Cities of Laval and Metropolitan Area of Québec, 1983)



other patients. This can be illustrated further by referring to the fact that after the first 28 days in 1983, only 14 percent of those with no visit in 1981 had visited a physician, as had 12 percent of those with only one visit in 1981, 16 percent of those with two visits in 1981, 25 percent of those with three to five visits in 1981, and 47 percent of those with six visits or more. The medians of the number of days before a use occurs show the same tendency, with 143 days before a visit having occurred for those with no visit in 1981, 119 days for those with one visit in 1981, 101 days for those with two visits, 72 days for those with three to five visits and 32.5 days only for those with six visits or more.

A test is available, using regression methods (Lee, 1980), to identify among four distributions the one that reproduces best the form of hazard rates distribution. Partial results of this test are found in Table 2. Four models are used to reproduce the curves found in Figure 1. The exponential model assumes that hazard rates are constant over time, while the three other models (the linear logistic model, Gompertz model, and Weibull model) assume that the hazard rates are time dependent.

Table 2 shows the statistics for choosing among models for the distribution of hazard rates in five levels of utilization. Part A of each of the subtables tests whether the time-dependent models are significantly different from the exponential model. The X^2 test with one

Table 2: Statistics for Choosing an Explicit Model for Hazard Rates, Given the Level of the 1981 Utilization

Test of the Exponential Model					*Significance of Each Model*				
Criterion		*Tested Model**			*Criterion*		*Tested Model†*		
	ln-L'₁		*ln-L'₂*	*X²*		*ln-L₁*		*X²*	p-*Level*
No Visit									
EXP	-715.54	Linear	-691.93	47.82	Sample	-676.72	EXP	77.64	0.00
		Gompertz	-684.96	61.16			Linear	30.42	0.00
		Weibull	-698.71	33.66			Gompertz	16.48	0.09
							Weibull	43.98	0.00
One Visit									
EXP	-523.40	Linear	-510.49	25.82	Sample	-499.14	EXP	48.50	0.00
		Gompertz	-510.08	26.64			Linear	22.68	0.01
		Weibull	-514.43	17.94			Gompertz	21.86	0.02
							Weibull	30.56	0.00
Two Visits									
EXP	-330.19	Linear	-322.56	15.26	Sample	-318.51	EXP	23.36	0.01
		Gompertz	-321.90	16.28			Linear	8.10	0.46
		Weibull	-323.76	12.86			Gompertz	6.78	0.66
							Weibull	5.25	0.81
Three to Five Visits									
EXP	-463.66	Linear	-461.97	3.38	Sample	-451.68	EXP	23.96	0.01
		Gompertz	-460.03	7.26			Linear	20.58	0.01
		Weibull	-462.01	3.30			Gompertz	16.70	0.05
							Weibull	20.66	0.01
Six Visits or More									
EXP	-252.49	Linear	-251.11	2.76	Sample	-245.35	EXP	14.68	0.14
		Gompertz	-250.44	4.10			Linear	11.52	0.24
		Weibull	-248.71	7.56			Gompertz	10.18	0.34
							Weibull	6.72	0.67

* $X^2 = -2\,[\,(ln\text{-}L'_1) - (ln\text{-}L'_2)]$.
† The $ln\text{-}L_1$ are the $ln\text{-}L'_1$ in these cases.

degree of freedom is used to assess this difference. The results of this test should make it clear that the exponential model is not significantly different from some of the time-dependent models in the case of the three to five visits and in the case of the six visits or more. Part B of the subtables assesses whether the four models reproduce adequately the observed distribution of hazard rates. The exponential model is accepted only in the case of six visits or more, while the Gompertz model is acceptable at the .05 level in three out of the four other cases.

In the case of the one-visit level, the p level of the Gompertz model is .02, the highest p level in this case. The Weibull model has the lowest X^2 statistic at the two visits and at the six visits or more. Across the four first levels of utilization in 1981, the Gompertz model is the one which is most often accepted—and considered adequate. Although two out of the three time-dependent models are significantly different from the exponential model at the level of the six or more visits, the exponential model is acceptable at the .14 p-level. Also, it is remarkable that as the level of utilization in 1981 grows, the X^2 statistic for the exponential models goes from a high of 77.64 to a low of 14.68. Hence, there is some evidence that the exponential model fits the hazard rates better and better as the level of past utilization increases.

Consequently, it seems that utilization by individuals with a low level of past utilization is time dependent. The form of these distributions in Figure 1 shows that the propensity on the part of these individuals to use medical care increases as time passes. But at a higher level of past utilization, utilization is not time dependent; in these cases, the propensity to use medical care is stable. Wolinsky and Coe (1984) have suggested that the variables explaining high utilization level might be different from variables explaining low or medium utilization levels. We have seen here that the pattern of utilization itself is different. It is the way the dependent variable is conceptualized that changes when one passes from a low/medium level of utilization to a high level of utilization.

The reading of cumulative hazard rates distribution for subgroups also allows identification of the ranges over which the subgroups differ in their propensity to use medical care. Table 1 shows that the sexes did not have different levels of propensity. In Figure 2, the plot of the hazard rates for each of the genders shows that beginning at about the 120th day through to the 250th day, females had a higher propensity to use care than males, while the reverse was true past the 250th day.

Three regression models were run on a subsample consisting of individuals who had used medical services between the 120th through to the 250th day of 1983. The results are shown in Table 3. Here, sex is a significant predictor of utilization in the case of the Cox survival model only. For the logistic and linear regression models, the point at which the sampled individuals were classified as users was fixed at the 180th day. Thus, if a survey asked individuals if they had used a medical care service in the 60 days before the interview (180 - 60 = 120), then sex would not have been retained in the analysis of the data as a predictor of utilization. The Cox regression model and the plot of the cumulative hazard rates have shown that the difference between the

Table 3: Study of the Effect of Sex and the 1981 Utilization for the 120th through the 250th Day in 1983

(1) *Independent Variable*	*(2)* *Coefficient*	*(3)* *Standard Deviation*	*(4)* *Ratio (2)/(3)*
Cox Survival Model			
Sex	-.2470	.1223	-2.0188
Utilization in 1981	.0384	.0205	1.8775
Logistic Linear Model			
Sex	-.1277	.1251	-1.021
Utilization in 1981	.0739	.0483	-1.529
Linear Regression Model			
Sex	-.0615	.0610	
Utilization in 1981	.0164	.0105	

sexes is very limited, but does exist. This pattern may account for some of the divergence found in the literature concerning the effect of sex on utilization (Hulka and Wheat, 1985; Evashwick et al., 1984; McCall and Wai, 1983).

DISCUSSION AND CONCLUSION

The concept of propensity to use health care has been proposed here as a useful descriptor of health care utilization. The definition of this concept as "the instantaneous probability to use a health service in a period, given that no use had occurred" allowed us to suggest that life table methods might be used to study the effect of independent variables on utilization. An empirical study of utilization on a sample of patients illustrates the point that results from the Cox survival model, the logistic linear model, and the linear regression model might differ.

Life table methods also make it possible to analyze the form of propensity distribution to use health care for substrata in a sample. In this way, explicit forms of propensity distribution can be identified and used directly in the analysis of the effect of a set of variables on utilization. These explicit models are more satisfactory than the distribution-free Cox survival model because they take into account the form of the distribution that generates the propensity to use health care. These forms are not theoretically neutral in the sense that they reveal whether propensity depends or does not depend on time.

With the data set available to us it was not possible to delineate episode of medical care. Thus, to control for possible left-censuring effect, only individuals without use for a year were included in the analysis. This period of time was rather long, but we preferred at this stage of the research process to err on the side of prudence regarding left-censoring because its effects were unknown, while by the same token, we would take the risk of choosing a bias sample, with known biases. The ideal would have been to have data sets with both the date at which visits occur and delineated episodes of care—but we were more often than not short of an ideal situation. Here, the requirement that one year without utilization be observed for each individual reduced the effect of the predictors on utilization. But there is no reason to believe that this dampening effect would vary in the three models evaluated here, while a left-censoring effect would have affected mainly the Cox survival model. It was deemed desirable to avoid the latter to increase comparability among the three models. Also, utilization in 1981 was the only independent variable significant in the Cox, logistic, or linear models. Clearly, this result was partially dependent on the fact that the number of independent variables available in the data set was limited. An extended test of the three models would require the introduction of predictors of utilization currently identified in the literature.

In social science literature, survival table analysis has a close kin in events history analysis (Tuman and Hannan, 1984). These models are not new, as they were presented in 1964 by Coleman and were used to study social mobility tables (Spilerman, 1972 and 1977). They are receiving more and more attention from researchers interested in a growing number of fields (Diekmann and Mitter, 1984). Their introduction into the field of health care services utilization seems promising from our point of view. The data available to researchers in this field are congenial with these methods, while they encourage theoretical reflection on the nature of utilization. In any case, it may be time to put less energy into replicating utilization studies that yield low percentages of explained variances and more energy into using methods that oblige one to see utilization as a pattern of events that are generated through time. More efficient models that parametrize this process of generating events may stem from such research.

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