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AN AUDIENCE FLOW MODEL OF TELEVISION VIEWING CHOICE

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A model for the prediction and explanation of individual television viewing choice is presented, incorporating considerations of utility, audience flow, and audience segmentation. The proposed model provides a quantifiably explicit theoretical explanation of television viewing choice, and its validation on large-sample network viewing data provides a baseline degree of accuracy against which the performance of future television viewing models may be compared. Of direct relevance to advertising agencies and the television networks is the suitability of the model for estimating the comparative impact of alternative programs on the audience size and composition of competing programs in the immediate and subsequent time slots.

(Television Viewing; Audience Exposure; Advertising; Television Program Scheduling)

1. Introduction

In 1981 an estimated 10 billion dollars were spent by television advertisers (*Advertising Age* 1982). With advertising production costs and other costs figured in, the total investment in television advertising was even larger than that. Since viewing choice has a substantial impact on the ability to attract and effectively allocate these dollars, it is very important to both the advertisers and the television industry that television viewing choice be better understood. In addition, the many new choices made possible by the proliferation of cable and other new video technology make such an understanding of viewing choice especially timely.

Viewing choice may be described at either the aggregate level or the individual level. Recent advances in aggregate ratings estimation have been proposed by Horen (1980) and Gensch and Shaman (1980a, b). Horen's model uses past ratings data and other program attributes to predict future program ratings. The ratings model is then used as a basis for choosing optimal program scheduling from the network's perspective.

The Gensch and Shaman model uses a trigonometric time series approach to estimate the aggregate television audience at different days, hours, and seasons. An important conclusion from the accuracy of their model is that the aggregate television audience is highly predictable, and does not appear to be much affected by which programs are being shown.

One may infer from this empirical generalization that the viewing choice process may be usefully considered as a two-stage process. In stage one, the individual chooses whether or not to watch, and in stage two determines which program to view. The Gensch and Shaman results imply that the first stage can be effectively predicted, and

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that the two stages may be modelled independently. This paper proposes a method of modelling the second stage of the viewing choice process.

To model this choice stage of television viewing, however, it is necessary to describe behavior at the individual level. Many aggregate audience exposure models have been proposed which acknowledge different exposure probabilities for each individual (e.g., Greene and Stock 1967; Chandon 1976; Rust and Klompmaker 1981). Evidence that these exposure probabilities are nonstationary (Schreiber 1974) has led to nonstationary exposure models (Sabavala and Morrison 1981). All of these models clearly reflect the fact that individual differences occur in viewing choice. Much less is known, however, about why these differences occur.

Consideration of past research in viewing choice suggests a useful conceptual framework for building an individual viewing choice model. The proposed model integrates the concepts of utility, audience flow, and audience segmentation.

Lehmann (1971) developed a utility model which used variables related to program type and quality of production to predict the preference of television shows. The model did not predict viewing behavior as such, but suggested profitable directions for the development of viewing choice utility models.

Viewing choice involves more than just preference, because the channel to which a television set is currently tuned will tend to remain on, unless effort is expended to change the channel. For purposes of consistency, this paper will refer to these effects of channel inertia and lead-in as "audience flow" effects.

Horen (1980) made a partial allowance for these effects by including a lead-in variable in his aggregate model. Other current research explores the use of Markov chains to model audience flow phenomena (Zackon 1981). It is possible to integrate conceptually audience flow effects into a utility framework, if it is assumed that the effort expenditure required to change channels involves some disutility.

The viewing behavior of audience segments has been another fertile area of research (Bower 1973; Gensch and Ranganathan 1974; Villani 1975; Goodhardt *et al.* 1975; Frank and Greenberg 1979, 1980). Consistent with the spirit of this past research, the proposed model assumes that individuals within a viewing segment possess similar viewing option utilities, given that audience flow effects are held constant.

The purpose of this paper is to develop and test a model of individual viewing choice. The model incorporates utility, audience flow, and audience segmentation, and is tested on large-sample network television data.

§2 presents the assumptions and formulation of the model, and §3 discusses the model's estimation. §4 describes the data, the results of estimating the model, and the results of a large sample cross-validated predictive test. §5 includes conclusions, an illustration of the model's use, and a discussion of the managerial implications and limitations of the model.

2. Model Description

2.1. *Assumptions*

Let us denote the utility of viewing half-hour program segment (viewing option) v to individual i as $u(i,v)$, with corresponding probability of choice $c(i,v)$. Consistent with the Luce axiom (Luce 1959, 1977) we assume that the probability of individual i viewing half-hour program segment v^*, given that he or she has chosen to watch television that half hour, is:

$$c(i,v^*) = u(i,v^*) \Big/ \sum_{v \in S} u(i,v) \tag{1}$$

where S is the time slot corresponding to v^*.

The model segments the population by age, education, and sex. With these divisions, there are eight ($2 \times 2 \times 2$) demographic segments (Table 1)—although other splits and segments could be explored if desired. For reasons of parsimony and ease of estimation, the viewing segments are assumed to be homogeneous in the construction of utilities. Thus, two individuals from the same segment, other factors being equal, would be assumed to have the same choice probabilities.[1]

Programs are assumed to be classifiable into one of nine program types: serial drama, action drama, psychological drama, game show, talk, variety, movie, news, sports or comedy. These program types are similar to ones found by factor analysis[2] (Gensch and Ranganathan 1974) and have previously been used to significantly improve the estimation of television audience duplication (Headen, Klompmaker, and Rust 1979). Utilities derived from the particular program types are allowed to vary across the segments. The model assumes that different program types may have different utility to different segments. Hence a distinct set of program type utilities is estimated for each segment.

There are assumed to be six "flow states" which may affect the utility of a viewing option (see Table 2). A separate flow state exists for each combination of individual and viewing option in a particular half-hour period. The flow state incorporates information as to whether the television was off or on already; if the set was on, whether it was tuned to the same channel on which the viewing option is appearing; and whether or not the viewing option is the continuation of a program already in progress. To reduce computational requirements, the utilities derived from these flow states are assumed for this demonstration to be constant across the segments.

As an example of how a flow state may be expected to affect utility, consider the fourth flow state (see Table 2). The set is already on, and it is tuned to a channel different from that on which the viewing option represents the continuation of a program. It would seem reasonable to expect the utility of this flow state to be low.

Summarizing, the model assumes that the probability of choice corresponding to an

TABLE 1

Description of Segments

Segment	Description		Count	Sum of Weights	Abbreviation
1 older (≥ 35)	uneducated (≤ 11 yrs)	women	170	564.4	(OUW)
2 older	educated	women	938	2,420.0	(OEW)
3 younger	uneducated	women	574	1,968.8	(YUW)
4 younger	educated	women	1,357	2,727.6	(YEW)
5 older	uneducated	men	81	426.1	(OUM)
6 older	educated	men	780	2,410.2	(OEM)
7 younger	uneducated	men	371	1,691.8	(YUM)
8 younger	educated	men	1,163	2,256.2	(YEM)

[1]Some confidence in the validity of the assumption of demographic segment homogeneity in choice probabilities may be drawn from the results of variations in program choices between vs. within segments. Multivariate analysis of variance found significant variations among segments in terms of the relative probabilities of individuals within segments viewing the nine program types (Wilks' Lambda = 0.71, significant at beyond 0.001). Hence, the variation between segments was significantly greater than the variation within segments in choice behavior. Inspection of relative frequencies of program viewing across segments shows a generally expected pattern of viewing behavior (e.g., "sports programs far more likely to be viewed by males than by females of all education levels," and so forth).

[2]The factor analysis approach to defining program types has not been without controversy. While Kirsch and Banks (1962), Wells (1969), and Frank, Becknell and Clokey (1971) arrived at results similar to those of Gensch and Ranganathan, Ehrenberg (1968) was unable to discover the meaningful program types using factor analysis.

TABLE 2

Description of Flow States

Flow State	Description			F_1	F_2	F_3	F_4	F_5
1	set on	right channel	start	1	0	0	0	0
2	set on	right channel	continuation	0	1	0	0	0
3	set on	wrong channel	start	0	0	1	0	0
4	set on	wrong channel	continuation	0	0	0	1	0
5	set off		start	0	0	0	0	1
6	set off		continuation	−1	−1	−1	−1	−1

individual and viewing option is predictable using the individual's demographic segment, the program type of the viewing option, and the flow state corresponding to the individual and viewing option.

2.2. *Formulation*

The utility of viewing option v to individual i may be viewed as a mean utility plus a deviation from the mean. In other words, variables relating to the viewing option and the individual may be used to explain why a particular program has more utility than average or less utility than average to an individual at a particular time. The model specifies explanatory variables to explain these deviations. The model is formulated as a regression model with effect coded variables (Kerlinger and Pedhazur 1973). Effect coding is a variation of dummy variable coding which allows interpretations similar to that of analysis of variance.

The flow state variable **F** (see Table 2) is a vector corresponding to viewing option v and individual i, which reflects whether the television was previously on or off; if it was on, whether it was tuned to the same channel as v; and whether v is the start or continuation of a program. For example, if the set has just been turned on, and viewing option v is the start of a program, then flow state 5 applies. The fifth element of **F** would be 1 and the other elements would be 0. Since the vector is used to determine utility deviations from the mean, the sixth and last flow state would be coded as -1 for each of the five elements of **F**.

The program type variable **T** is a vector corresponding to viewing option v and individual i, which reflects the segment of individual i and the program type of viewing option v. If there are n_s segments and n_t program types, then **T** is of length $(n_s \cdot n_t) - 1$. The vector **T**, like **F**, is effect coded. Thus, the intersection of segment n_s and program type n_t would result in -1 for all of the elements of **T**. Otherwise, the intersection of segment s and program type t would result in elements $n_s(t-1)+s$ of **T** being equal to 1, while the rest would be 0.

Using the variables defined above, it is possible to express concisely the utility of viewing option v to individual i:

$$u(i,v) = \bar{u} + \mathbf{B}_1\mathbf{F} + \mathbf{B}_2\mathbf{T} + \epsilon_{iv} \tag{2}$$

where $\bar{u}$ is the overall mean utility across the groups defined by variables **F** and **T**, where **F** and **T** are defined as above, ϵ_{iv} represents the unexplained deviation (assumed to be normally distributed), and $\mathbf{B}_1$ and $\mathbf{B}_2$ are coefficient vectors.

3. Estimation

Each individual in the television sample used here (Simmons 1978a) has a sampling weight, which is inversely proportional to that individual's probability of selection. To produce estimates for the population using the above model, it is necessary to incorporate these weights into the analysis. The resulting appropriate statistical methodology is weighted least squares regression with effect vectors, where the weights are the sampling weights.

This effect coded regression is formally identically to analysis of variance. The regression formulation is used to handle more easily the computational complications caused by the weighted observations and the fact that the analysis of variance would involve a difficult unbalanced incomplete block design.

Also, regression using effect coded variables has several desirable properties (summarized from Kerlinger and Pedhazur 1973):

1. Each element of the coefficient vector represents a deviation from the overall mean.

2. Similar to analysis of variance, a predicted score is the sum of the overall mean and the appropriate coefficient vector elements.

3. The analysis of data with unequal cell sizes (such as appear in this paper) proceeds in the same manner as that for equal cell sizes.

The coefficient vector elements may be usefully interpreted as utility deviations. For example, the first element of $\mathbf{B}_2$ reflects the deviation from mean utility attributable to program type 1 for segment 1. If the first program type is relatively unappealing to segment 1, for example, the respective element of $\mathbf{B}_2$ would be negative.

In order to use the model predictively, it is first necessary to estimate the coefficients of the model. The dependent variable, $u(i,v^*)$, is not observable. Thus, it is necessary to approximate $u(i,v^*)$, using (1), which may be reexpressed as:

$$\hat{u}(i,v^*) = c(i,v^*) \sum_{v \in S} u(i,v). \tag{3}$$

The quantity $\sum_{v \in S} u(i,v)$ may be considered a measure of the relative attractiveness or strength of v's time slot. If the quantity is large, then the implication may be that two or three high-utility programs are being shown then. A viewing option may have high utility, but still have a mediocre probability of being viewed if it is competing against other high-utility options. Conversely, even a low-utility program might fare reasonably well in a weak time slot.

Thus, if information were known on the strength of the time slots, the viewing choices could be more reliably used to estimate utility. If the (temporary) assumption is made that the time slots are of equal strength, and the arbitrary value of 1 is chosen as the sum of the utilities in each time slot, then we have:

$$\hat{u}(i,v^*) = c(i,v) \cdot 1 = c(i,v). \tag{4}$$

Since large-sample estimates of $c(i,v)$ may be obtained directly from panel data, the assumption of equal strengths for the time slots implies that regression may be employed to estimate the coefficients of the model.

However, once the coefficients are estimated, they may be used to reestimate the utility of each viewing option:

$$\hat{\hat{u}}(i,v^*) = \bar{u} + \mathbf{B}_1\mathbf{F} + \mathbf{B}_2\mathbf{T}. \tag{5}$$

Then, using the above reestimated utilities, the relative strength $k(S)$ of each time slot S may be reestimated:

$$\hat{k}(S) = \sum_{v \in S} \hat{\hat{u}}(i,v). \tag{6}$$

The relative strengths of the time slots enable the reestimation of each viewing option's utility:

$$\hat{u}(i,v^*) = \hat{k}(S) \cdot c(i,v^*). \tag{7}$$

The new estimates may then be used as the dependent variable values for a new regression. The new coefficient estimates then obtained should be better, since the revised dependent variable takes into consideration improved estimates of the relative strengths of the time slots. This procedure is repeated until the coefficient values converge. A flow chart of the iterative procedure is presented in Figure 1.

In the first iteration the dependent variable is the audience share (in proportions) for the viewing options in a particular time slot for a particular combination of segment and prior program (or none). The prior program (or none), combined with a current viewing option, defines the flow state variable **F** (Table 2). The segment, combined with the program type of a viewing option, defines the program type variable **T**. The

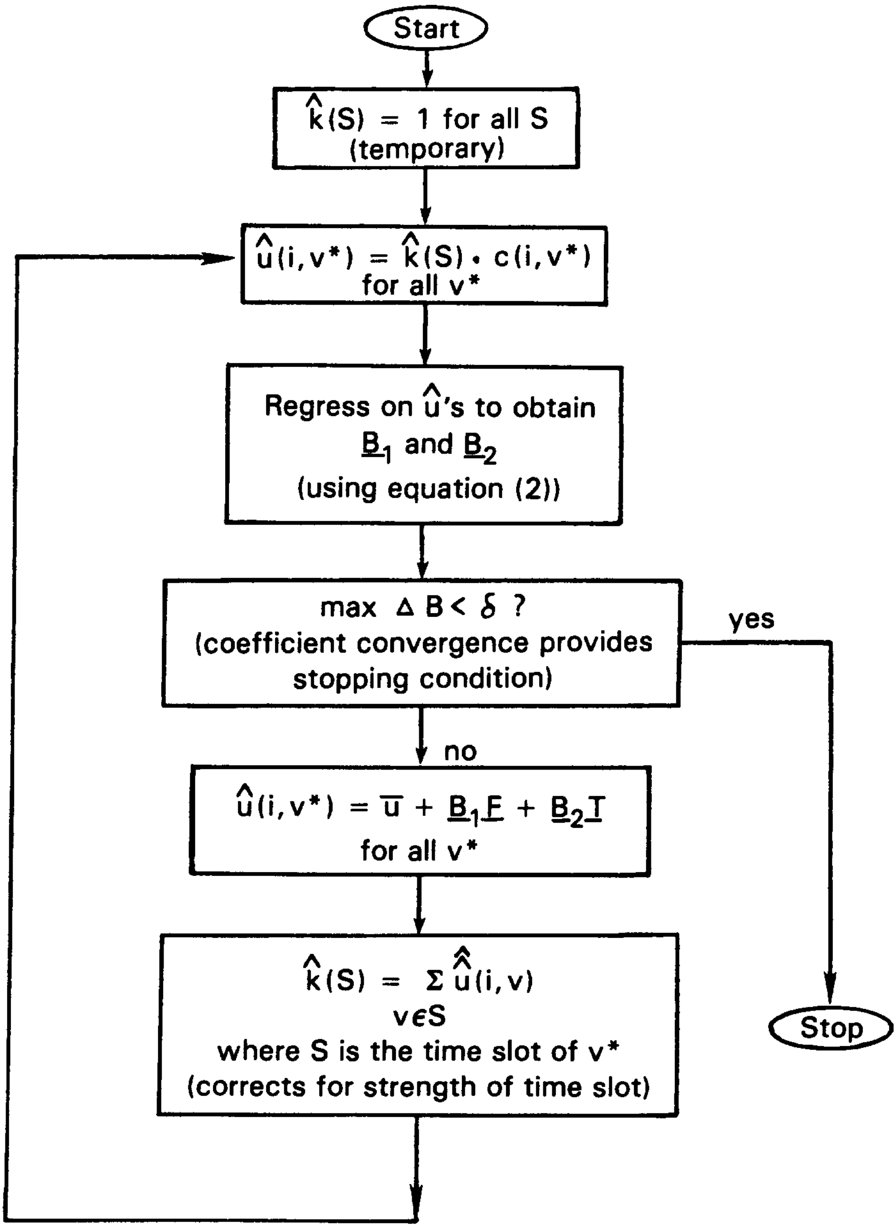

FIGURE 1. Iterative Estimation Procedure.

unit of analysis is the intersection of segment and prior program (or none). For each unit, there is a separate data point corresponding to each viewing option. In this estimation, 895 data points result from the combinations of time slot, prior program, and viewing option, with each data point comprised of many individuals who share the same independent variable values.

The estimation performed at each step of the iterative procedure is mathematically equivalent to using the individual as the unit of analysis. It is for computational convenience that individuals are aggregated by segment and prior program (or none) viewed. A weighted least squares regression is performed, in which the weight for a particular segment and prior program combination is the sum of the sampling weights for the individuals in that segment who viewed that particular prior program.

The coefficients obtained using this method of aggregation are identical to those which would be obtained without aggregating, but the R^2 is necessarily higher (Kmenta 1971, pp. 325–328). The R^2 from the aggregated analysis may provide a truer picture of the accuracy of the model (Morrison 1972; 1973). In any event the choice of reported R^2 does not affect the major findings of this paper.

4. Empirical Analysis

4.1. *Data*

The data used to estimate and test the model were collected by Simmons (1978a, b). Their respondents were selected using a national multi-stage area cluster sample. Television viewing data were collected from 5,652 respondents in the Fall of 1977, of which 5,434 were usable respondents for this study.

4.2. *Estimation Results*

The model coefficients were estimated using the prime time program data for Monday and Thursday. There were 12 half-hour time slots, involving 34 viewing options[3] and 18,522 individual viewing choices.

The iterative procedure converged after eight iterations, yielding the final coefficient values reported in Table 3. The first iteration, in which viewing share was the dependent variable, an adjusted R^2 of 0.85 was obtained. Thus the model provides good explanation of viewing choice, even without iteratively adjusting for the relative strength of the time periods.

Subsequent iterations progressively refined the dependent variable to more closely correspond to utility, using equation (3). By the eighth iteration the adjusted R^2 had risen to 0.93. Because an iterative procedure is employed, and the dependent variable is not directly observable, many of the usual interpretations of R^2 may not be made. Nevertheless, the high R^2, coupled with the trend of the fit accuracy increasing over the iterations, is a reassuring check of the internal consistency of the model.

Because the iterative nature of the analysis may produce dependencies, the usual hypothesis tests on the variables may not strictly be performed. The model's accuracy must be assessed on the basis of its accuracy of prediction in a large sample cross-validation (see §4.3).

However, some insight may be gained if one assumes that the dependent variable in the final iteration is an independent and valid measure of utility. This assumption may

[3]The programs in the estimation sample included 6 action dramas, 10 psychological dramas, 5 movies, 8 comedies, and 5 sports programs. Since the programs were chosen from prime time, it is not surprising that no serial dramas or game shows (normally shown in the morning), variety/talk shows (normally shown in the late evening), or news shows (normally shown in the early or late evening) were encountered in the estimation sample.

TABLE 3

Regression Coefficients from Final Iteration

Flow State	Coefficient B_1
1	− 0.094
2	0.814
3	− 0.275
4	− 0.310
5	0.036
6	− 0.171 ($= -\Sigma B_1$)

Program Type Coefficients B_2

Segment	Action Drama	Psychological Drama	Comedy	Sports	Movie
1 (OUW)	− 0.139	0.109	− 0.019	− 0.070	0.020
2 (OEW)	− 0.130	0.080	− 0.030	− 0.018	0.046
3 (YUW)	− 0.098	0.012	− 0.018	− 0.092	− 0.070
4 (YEW)	− 0.102	0.009	0.026	− 0.029	0.011
5 (OUM)	− 0.115	0.045	− 0.043	0.157	− 0.001
6 (OEM)	− 0.074	− 0.020	−0.073	0.148	− 0.034
7 (YUM)	0.029	0.075	0.001	0.157	0.025
8 (YEM)	− 0.075	− 0.040	−0.041	0.244	0.137 ($= -\Sigma B_2$)

not be too bad, considering the rise in R^2 over the iterations, and the intuitive justification for the dependent variable adjustment in the iterative procedure.

Given this assumption, the significance of the variables may be tested using nested F tests of the incremental gains in explained variance (Namboodiri *et al.* 1975). Using degrees of freedom adjusted to reflect the weighted nature of the analysis, both the flow state variable **F** and the program type variable **T** are found to be significant at the 0.01 level.

Further (face) validity checks are provided by an examination of the signs and magnitudes of the flow state coefficients. All are as would be anticipated. For example, the second flow state has a large positive coefficient. This flow state corresponds to a situation in which the set is already on, tuned to the right channel, and the viewing option represents the continuation of a program; e.g., someone is in the middle of watching a program. It seems reasonable to associate a relatively high utility with the program's continuation.

Examination of the program type coefficients provides a further validity check. Once again, they appear to be quite reasonable. For example, the highest utility increment is associated with the intersection of the eighth segment (young educated men) and sports programming. The advertising profession has long known that sports programming is attractive to this economically important market segment. The week-end time slots when large numbers of young educated men are watching have long been used by networks for sports programming. It is also interesting, and entirely expected, that all of the women segments have a negative utility deviation associated with sports.

4.3. *Prediction Results*

The model's ability to predict individual viewing choice was tested using prime time programs on Wednesday and Friday. These days were chosen in an attempt to pick typical days of the week while minimizing overlap with the programs used to estimate the model. Different weeks were used, to further maximize the difference between the estimation programs and the validation programs. There were 12 half-hour time slots used in the validation, involving 30 viewing options[4] and 19,050 individual viewing choices.

At every time slot, the viewing choice made by each individual was compared to the choice predicted by the model, based on the individual's segment and flow states (taking into account the individual's viewing choice the previous half hour), and the program types of the program alternatives.

Three simple models were also tested. The first model assumes random program choice. The second model assumes that an individual will choose randomly except that when he or she starts a program, he or she will watch it to the end. The third model assumes that an individual will first choose randomly, but then will stick with that program type, if possible. The predictive results of these four models are shown in Table 4. Z tests of the differences between the prediction proportions show that the proposed model predicted significantly better than each of the three simpler models at beyond the 0.01 level. The proposed model predicted viewing choice correctly 76% of the time (corresponding to a mean prediction error of 2 rating points), whereas the accuracy of the simpler models ranged from 41% to 65% (Table 4).

5. Conclusions, Implications, and Limitations

The proposed model is a successful predictor of individual viewing choice. Its 76% prediction accuracy represents a promising step in the effort to better understand this complex subject, an area marked by considerable economic importance and a paucity of previous empirical work. The empirical findings provide a baseline against which future models of individual viewing choice may be compared.

The theoretical framework also provides a foundation upon which other researchers in this area may build. The "audience flow" effects of lead-in and inertia of channel selection have been shown to improve prediction, as has the differential attraction of program types to the demographic segments of the viewers. While knowledge of these effects is not new, the proposed model provides a way of making these variables quantifiable and explicitly useful for explanation and prediction of individual viewing choice.

To exemplify the potential managerial usefulness of the proposed model to television networks and advertising agencies, let us consider the evaluation of the impact on audience of a proposed schedule change. We assume that the existing program will be (or might be) replaced by an alternate program whose program type is known.

The researcher evaluating this programming shift using the proposed model would perform the following steps:

1. Estimate seasonally-adjusted aggregate audiences for each network and time slot, by segment. Existing models (Gensch and Shaman 1980a, b) have been shown to produce accurate estimates.

2. Estimate the proportions turning the television on or off which produce the incremental changes in aggregate audience. These proportions may be approximated using historical Nielsen or Simmons data.

TABLE 4

Predictive Accuracy of Four Viewing Models

Model	Description	Proportion of Correct Predictions
1	Proposed model	0.762
2	"Random choice"	0.406
3	"Watch until program conclusion"	0.646
4	"Stay with a program type"	0.591

[4]The validation sample consists of 12 action dramas, 2 psychological dramas, 10 movies, and 6 comedies.

TABLE 5

Estimated Audiences for Example Program Substitutions

		Current		Revised	
	Segment	("Grizzly Adams") Predicted	Actual	(Psych. Drama) Predicted	(Sports) Predicted
NBC Segment Audiences	1 (OUW)	0.09	0.10	0.14	0.10
[Proportion of Segment in NBC Viewing Audience]	2 (OEW)	0.07	0.10	0.11	0.09
	3 (YUW)	0.09	0.07	0.12	0.10
	4 (YEW)	0.08	0.05	0.09	0.09
	5 (OUM)	0.09	0.11	0.13	0.15
	6 (OEM)	0.08	0.10	0.09	0.11
	7 (YUM)	0.07	0.09	0.08	0.09
	8 (YEM)	0.07	0.05	0.08	0.11
Aggregate Audiences	Network				
[Proportion of Total Viewing Audiences]	NBC	0.08	0.08	0.10	0.11
	ABC ("Eight is Enough")	0.10	0.12	0.11	0.10
	CBS ("Good Times")	0.10	0.08	0.07	0.07

3. From steps 1 and 2, the number of viewers of the time slot in which the schedule change is planned has been approximated for each combination of segment and prior program (or none) watched. Equation (1) may now be used to estimate, for each combination of segment and prior program, the proportion which will view each of the programs in the revised time slot.

4. Step 3 may be successively repeated for subsequent time periods to provide an idea of the effects of the switch on later time periods. The model implies that the *later* time periods' audiences will be affected by an earlier program change, due to the lead-in aspect of the flow state variable.

5. If the network is evaluating the programming shift, it may examine the results of several different program types, choosing to substitute a program type which will both result in a high rating for that half hour and provide an effective lead-in to the network's subsequent programs.

Table 5 presents an illustration of the results of applying this procedure to predicting audience proportions for a possible change in the program schedule for a given time slot. Applying the model using the estimated proportions of each segment watching television during this time slot, as well as the coefficients from the estimation sample, produced the predicted audience for the NBC show "Grizzly Adams" and its competitors. One may note that the predicted audiences were close to those actually observed.[5]

[5]The aggregate audiences do not sum to one because there are nonviewers in the population. Also the numbers reported here are somewhat lower than those typically encountered in Nielsen audimeter data, due to the fact that they were tabulated from viewing diaries.

Predicted vs. actual audiences broken down by demographic segment are shown for the NBC show (the others are omitted for brevity).

Schedule changes are evaluated for two proposed revisions, both of which result in higher predicted ratings for NBC. Replacing "Grizzly Adams" with a psychological drama would be predicted to increase the audience from 0.08 to 0.10, and replacement by a sports program would result in even more of an increase (to 0.11). Which of these moves might be preferred by NBC would depend not only on costs and expected aggregate ratings, but also the expected appeal of each replacement to the audience segments of interest to NBC's advertisers. One could weight the proportions of each segment by the number estimated as viewing at this time, to determine not only the aggregate audience ratings, but also the audience composition delivered to advertisers. In this case, advertisers seeking male target markets may prefer the sports program, while females may be better reached with the psychological drama. These changes in the segment audiences also affect the lead-in to subsequent time slots.

As an extension to the proposed model, the relative attractiveness of programs might be used to revise the audience estimates. One preliminary method of doing this might be to use the residuals from equation (2). An unusually attractive program within a program type would be expected to have a large positive residual.

Some limitations of the model should be noted. The model is tested on network viewing data. It is conceivable that an empirical test including cable programs and local programs may have been less successful. Nevertheless, the model may easily be applied to these expanded alternative sets, and expanded if necessary to include variables specific to the inclusion of cable and/or local programs.

Very popular programs will tend to have underestimated choice probabilities, since programs within a program type are assumed to have equal utility to a given segment. This problem may be remedied for returning programs by including a program-specific variable based upon historical data.

The model does not explain why individuals turn the television on. This is an important issue for further research. Also, all of the traditional limitations of diary data qualify the validity of the empirical results, as does the fact that the data used may not necessarily be representative of data gathered from other days, seasons, or years.

The proposed model provides an explicit model basis for future research in television viewing choice, and suggests a systematic method for considering the comparative impact on both immediate and subsequent audience size and composition of alternative programs within specified time slots.[6]

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[6]This paper was received April 1981 and has been with the authors for 3 revisions.

References

Advertising Age (1981), (February 16), S-4.

Bower, Robert (1973), *Television and Public*, New York: Holt, Rinehart, and Winston.

Chandon, J. L. J. (1976), "A Comparative Study of Media Exposure Models," unpublished Ph.D. Dissertation, Northwestern University.

Ehrenberg, A. S. C (1968), "The Factor Analytic Search for Program Types," *Journal of Advertising Research*, 8, 55–63.

Frank, Ronald E., James C. Becknell and James D. Clokey (1971), "Television Program Types," *Journal of Marketing Research*, 8 (May), 204–211.

——— and Marshall G. Greenberg (1979), "Interest Based Segments of TV Audiences," *Journal of Advertising Research*, 19 (October), 43–52.

——— and ——— (1980), *The Public's Use of Television*, Beverly Hills: Sage.

Gensch, Dennis and B. Ranganathan (1974), "Evaluation of Television Program Content for the Purpose of Promotional Segmentation," *Journal of Marketing Research*, 11 (November) 390–398.

——— and Paul Shaman (1980a), "Predicting TV Ratings," *Journal of Advertising Research*, 20 (August), 85–92.

——— and ——— (1980b), "Models of Competitive Television Ratings," *Journal of Marketing Research*, 17 (August), 307–315.

Goodhardt, G. J., A. S. C. Ehrenberg and M. A. Collins (1975), *The Television Viewing Audience: Patterns of Viewing*, Saxon House.

Greene, J. D. and J. S. Stock (1967), *Advertising Reach and Frequency in Magazines*, New York: Marketmath Inc. and Reader's Digest Association.

Headen, Robert S., Jay E. Klompmaker and Roland T. Rust, "The Duplication of Viewing Law and Television Media Schedule Evaluation," *Journal of Marketing Research*, 16 (August), 333–340.

Horen, Jeffrey H. (1980), "Scheduling of Network Television Programs" *Management Science*, 26 (April), 354–370.

Kerlinger, Fred N. and Elazur J. Pedhazur (1973), *Multiple Regression in Behavioral Reserach*, New York: Holt, Rinehart and Winston.

Kirsch, Arthur D. and Seymour Banks (1962), "Program Types Defined by Factor Analysis," *Journal of Advertising Research*, 2, 29–31.

Kmenta, Jan (1971), *Elements of Econometrics*, New York: Macmillan.

Lehmann, Donald R. (1971), "Television Show Preference: Application of a Choice Model," *Journal of Marketing Research*, 8 (February), 47–55.

Luce, R. Duncan (1959), *Individual Choice Behavior: A Theoretical Analysis*, New York: John Wiley & Sons.

——— (1977), "The Choice Axiom After Twenty Years," *Journal of Mathematical Psychology*, 15, 215–233.

Morrison, Donald G. (1972), "Upper Bounds for Correlations Between Binary Outcomes and Probabilistic Predictions," *Journal of the American Statistical Association*, 67 (March), 68–70.

——— (1973), "Evaluating Market Segmentation Studies: The Properties of R^2," *Management Science*, 19 (July), 1213–1221.

Namboodiri, N. K., L. F. Carter and H. M. Blalock, Jr. (1975), *Applied Multivariate Analysis and Experimental Designs*, New York: McGraw-Hill.

Rust, Roland T. and Jay E. Klompmaker (1981), "Improving the Estimation Procedure for the Beta Binomial TV Exposure Model," *Journal of Marketing Research*, 18 (November), 442–448.

Sabavala, Darius J. and Donald G. Morrison (1981), "A Nonstationary Model of Binary Choice Applied to Media Exposure," *Management Science*, 27 (June), 637–657.

Schreiber, Robert J. (1974), "Instability in Media Exposure Habits," *Journal of Advertising Research*, 14 (April), 13–17.

Simmons Media Studies (1978a), *Selective Markets and the Media Reaching Them*, New York: Simmons Media Studies.

——— (1978b), *Technical Guide: 1977/1978 Study of Selective Markets and the Media Reaching Them*, New York: Simmons Media Studies.

Villani, Kathryn E. A. (1975), "Personality/Life Style and Television Viewing Behavior," *Journal of Marketing Research*, 12 (November), 432–439.

Wells, William D. (1969), "The Rise and Fall of Television Program Types," *Journal of Advertising Research*, 9, 21–27.

Zackon, Richard (1981), unpublished personal correspondence.