SESSION IX

USING COMPUTERS IN APPLIED SETTINGS

Paula Goolkasian, *Chair*

Behavioral assessment of eating patterns and blood glucose in diabetes using the Self-Monitoring Analysis System

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The Self-Monitoring Analysis System is a set of microcomputer programs that were developed to remove clinical judgment from the task of behavioral assessment using self-monitoring diaries. The program is written in Turbo Pascal and runs on MS-DOS (16-bit) or CP/M (8-bit) microcomputer systems. The program allows the user to custom design data bases with hundreds of binary, categorical, integral, and real variables. Full-screen data-entry forms can be custom designed, and random access files allow for flexible data entry and editing. The program makes extensive utilization of Pascal's very flexible data structure capabilities. Dynamic allocation of memory allows the program to maximize its use of available RAM. Data from a patient with diabetes is presented as a case study illustrating the system's utility.

Microcomputer applications are becoming increasingly important in clinical psychology. Such applications as automated test scoring and interpretation, computerized behavioral interviews, and clinical management data bases take many tedious tasks away from the clinician. The most exciting new applications are those that allow the clinician to perform tasks that were previously difficult or impossible to do. The on-line processing of psychophysiological data, for example, opens up new possibilities in the area of biofeedback.

Behavioral medicine is an area of psychology in which new microcomputer applications are being developed. This paper presents one such application, the Self-Monitoring Analysis System, and describes its use in the assessment of eating patterns and blood glucose control in diabetes.

SELF-MONITORING AND BEHAVIORAL ASSESSMENT

Behavioral clinical psychologists are interested in the assessment and modification of patients' behavior in the

natural environment. To further these aims, behavioral assessment was developed as an alternative to traditional personality assessment (Goldfried & Kent, 1972). In traditional personality assessment, behavior is treated as a sign of the individual's underlying personality. In behavioral assessment, behavior is treated as a sample of how the individual behaves under specific stimulus conditions. Methods of behavioral assessment, therefore, involve obtaining samples of behavior under stimulus conditions that are as close to real life as possible (Goldfried & Linehan, 1977).

A number of methods have been developed for obtaining behavior samples for assessment purposes. These methods include behavior checklists (Barlow, Abel, & Blanchard, 1977), behavioral interviews (Linehan, 1977), role playing tests (Freedman, Rosenthal, Donahoe, Schlundt, & McFall, 1978), direct observation of behavior (Dodge, Schlundt, Schocken, & Delugach, 1984), situational inventories (Levenson & Gottman, 1978), and self-monitoring (Nelson, 1977). Self-monitoring is a particularly promising technique in which the subject keeps an ongoing record or diary of behavior as it occurs in everyday situations. Self-monitoring often not only involves keeping track of target behaviors—such as social interactions (Twentyman & McFall, 1975), eating (Mahoney, 1974), and smoking (McFall, 1970)—but also allows the systematic collection of data about the antecedents and consequences of behavior. Collection of information on antecedents, behaviors, and consequences allows the psy-

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chologist to perform a functional analysis of behavior in which hypotheses about the environmental events that control the behavior are generated (Schlundt, 1985).

When clients keep a self-monitoring diary, a large amount of data is often generated. Typically, clinicians review the records and use clinical judgment to identify patterns and draw inferences about functional relationships among antecedents, behaviors, and consequences. Although the clinical review of self-monitoring records provides data that might not otherwise be obtained, clinical judgment is known to be subject to inaccuracies and biases (Meehl, 1954). Many studies across a diverse range of domains have shown that statistical prediction is typically more accurate and reliable than clinical judgment (Sawyer, 1966).

THE SELF-MONITORING ANALYSIS SYSTEM

The Self-Monitoring Analysis System (Schlundt, 1985, 1986, in press) is a microcomputer-based set of programs that was developed to remove clinical judgment from the analysis of self-monitoring data in behavioral assessment. The Self-Monitoring Analysis System Version 3.0 (SMAS-3.0) consists of three microcomputer programs written in Turbo Pascal (Borland International, 1985) that run on CP/M and MS-DOS microcomputers. CP/M is one of the most popular operating systems in use on 8-bit microcomputers, such as Kaypro IIs and IVs, Osbornes, and TRS-80s. MS-DOS is a widely used operating system for 16-bit microcomputers (IBM PC and compatibles). When Borland International makes a compiler available for 32-bit microcomputer systems (e.g., Macintosh), SMAS can be made available on these systems as well. Three major programs make up the SMAS system: SETUP, ENTER, and SUMMARY.

SETUP allows the user to design a data base that corresponds to the information collected by subjects in self-monitoring diaries. It enables the user to create hundreds of binary, nominal, integral, and real variables and allows the user to define and name the categories of binary and nominal variables. SETUP also allows the user great flexibility in the design of data entry screens. SETUP results in the creation of a file family definition that serves as a template for the creation of patient data bases.

ENTER enables the user to create, maintain, and modify self-monitoring data bases. Each patient's data is entered into a separate file that is identified by a unique three-letter data extension. ENTER implements a full-screen data entry routine and allows for random access of records in the data base for editing purposes. It also performs checks on values entered for each variable to guard against common data entry errors.

SUMMARY takes a file of data analysis commands and produces statistical analyses of patient data bases as its output. The commands that were implemented are those that produce results that will enable the clinician to iden-

Table 1
Commands Available in the SUMMARY program

Command	Action
CATPLOT	Plots the probability distribution of a categorical or binary variable.
INTCAT	Plots the mean values of an integer or real variable for each category of a categorical or binary variable and performs a one-way analysis of variance.
CROSSTAB	Produces a two-way contingency table that displays the association between two categorical or binary variables.
CORREL	Measures the association between two integer or real variables using Pearson correlation coefficient.
MULTI	Performs log-linear contingency table analysis and multivariate information analysis on three to seven categorical or binary variables.
EXCLUDE	Used to selectively exclude observations from an analysis.
LAG	Creates time-lagged variables for use in sequential analysis.
BREAK	Used in sequential analysis applications to detect breaks in behavior sequences.
QSCORE	Used to create new variables that are linear combinations of old variables.
REVERSE	Rescales integer variables. This is useful in scoring rating scales.
PLOTVARS	Generates a plot of the value of each of a user-specified set of variables for each record in the data file.
LIST	Generates a line printer listing of the data base.
DISPLAY	Allows the user to select variables for output to a disk file in ASCII format. This allows SMAS data bases to be used by other computer programs.
UPDATE	Merges newly created variables with old variables into a new file family.

tify behavioral patterns without having to rely on clinical judgment. Table 1 presents the available commands and their results. SUMMARY is written to allow for flexible repetitive processing of the members of a file family; that is, a single run of SUMMARY can produce individual analyses of self-monitoring data for up to 25 patients. A utility program, MERGE, allows data from any number of patients to be pooled for group analysis.

The statistical procedures implemented in SUMMARY provide a general set of routines for analyzing observational data (e.g., Schlundt, 1982). When behavior is observed over time, the individual behavioral observations often do not meet the statistical assumption of independent random sampling (see Schlundt & Donahoe, 1983). To overcome the problem of nonindependence, special sequential data analysis techniques must be used (Chatfield & Lemon, 1970). SUMMARY contains facilities for performing sequential analysis of the interaction of behavior and environmental events over time using Markov chains (Schlundt, 1985).

Programming Problems and Their Solution in the Development of SMAS

In developing any complex computer program, a series of decisions must be made in order to generate computer code that will accomplish the desired objectives. To illustrate this process and to give insight into the inner workings of SMAS, we present a number of these decisions and their solutions.

Programming language. The choice of what programming language to use when developing a complex computer application has far-reaching consequences. SMAS went through two earlier versions. Version 1.0 was written in IBM/System 23 BASIC. The problems with this choice were that the program ran only on the IBM-DATAMASTER (an 8-bit IBM microcomputer that preceded the 16-bit IBM PC) and that BASIC, an interpreted language, is very slow. Version 2.0 was rewritten in C-BASIC (a semicompiled version of BASIC that operates on CP/M and MS-DOS systems). This version of SMAS was faster, but the program had serious flaws in its implementation that made editing data files very difficult. Rather than fix these problems, Version 3.0 was rewritten in Turbo Pascal.

Pascal was chosen over BASIC for several reasons: (1) it is a true compiled language so that its execution speed is as fast as possible, (2) it offers much greater flexibility in creating data structures than does BASIC, (3) it allows for dynamic allocation of memory, and (4) it is a structured programming language that makes the job of translating algorithms into understandable computer code much easier than does BASIC.

Turbo Pascal is an extremely easy to use software development system. It is a menu-driven system consisting of an editor with the same command set as WORDSTAR for creating and modifying programs, file and memory management utilities, and the actual compiler. When the compiler encounters a syntax error, control is passed to the editor, which positions the cursor at the error in the program. When an execution error occurs, the system locates its source and passes control to the editor, which positions the cursor at the location of the run-time error. These features make the development and debugging of complex programs easy and quick.

Flexibility. One of the first decisions that had to be made concerning the writing of SMAS was the degree to which the program was to be flexible. Writing a program that takes data from a single diary and analyzes it would be relatively trivial. Writing a program that takes many diaries (some of which will be conceived of and developed years in the future) requires a much more complex program. The decision was made to create a very flexible system that could handle a variety of different kinds of diaries.

The solution to this problem was the program SETUP. SETUP creates a definition file that contains information on the number of variables, the name or type of each variable, and its location and field size on the data entry screen. So that changes in definitions could be made, the

definition file is created in ASCII format (words and numbers that can be edited and changed using a word-processing program).

When developing a program, it is difficult to anticipate all of its possible uses in the future. For example, the program must allocate space to store information about each variable that is declared. Pascal lets the user define constants at the beginning of the program that can be used to allocate space when arrays and other data structures are declared. For example, changing the number of variables that can be used at one time simply requires changing the value of a single constant, MAXVARS, at the beginning of the program. Changing this constant changes the size of all of the arrays that are used to keep track of the variables throughout the program.

Data entry. Since diaries generate large numbers of observations, much of the user's time will be spent entering data into the computer. In addition, experience in using Versions 1.0 and 2.0 proved that no data entry operator is infallible, making frequent changes to the data base necessary. It was decided that a separate data entry and data editing program would be developed. Since this program would be used frequently, the goal was to make it as easy as possible to use. This led to the development of a set of Pascal procedures implementing a full-screen data entry processor.

A full-screen processor presents the user with a screen containing a number of fields, with each field labeled with a variable name. The fields are blank when new data is being entered, and they contain the contents of the current record when the program is being used to edit data files. The cursor is initially placed in the first field. The entry operator begins to type numbers in the blank fields or make desired changes. Cursor arrows and control keys allow editing functions within fields and the movement of the cursor from one field to the next.

Turbo Pascal has a function that reads the last character typed at the keyboard. This character is then processed using the Pascal CASE statement. The CASE statement allows the user to specify a list of values or ranges of values and the kinds of actions to be taken depending on the value of the variable. For example, entering a number or letter causes the program to add that character to the string it is building for the current data field, prints the character on the screen, and then moves the cursor one space to the right to await entry of the next character. If the back arrow key is pressed, the cursor is moved one space to the left, and an internal pointer identifies the place in the current string that can be changed by the next keystroke. The final result is passing an array of entered strings back to the part of the program calling the data entry procedure.

Data file layout. Another problem encountered in developing SMAS was how to store data in disk files in an efficient and accessible manner. Efficiency refers to storing the most data in the least space, and accessibility means enabling the user to access any record in the data base at random (this is opposed to the simplest file struc-

ture, which allows only sequential access). The major problem encountered in implementing these specifications was created by the flexibility of the system. Since it is not possible to know the number and types of variables ahead of time, it was not possible to determine the record size needed until run time. Random access files in Pascal (and most other languages) require specification of the record size at compilation time. The ability to specify data structures at run time rather than at compilation time is known as *dynamic allocation*.

The dynamic allocation of the file structure was solved by creating a random access file that consists of five-character strings. At run time, the number of five-character strings per record is calculated, and this value is used to determine the starting location of each record in the file. Each five-character string is used to store the values of five binary or categorical variables, or one integral variable. Real numbers are stored in two consecutive five-character strings. This strategy allows categorical variables to have up to 128 values (the number of different ASCII characters). The program first packs all of the binary values into as few five-character blocks as possible, then all of the categorical, then all of the integral, and finally all of the real values. This algorithm effectively implemented dynamic allocation of random access data file structure. The program ENTER can be used to create, extend, and edit these dynamically allocated random access files. The main disadvantage of using this algorithm is that the data cannot be edited using a word processor so to read the data for use in other programs, special unpacking routines must be written. This is not a serious limitation, since the DISPLAY command of the SUMMARY program creates an ASCII file from a SMAS data base.

Dynamic allocation of RAM for data analysis. The SUMMARY program reads the data from the specially formatted data file, stores it in random access memory (RAM), and allows the user to analyze this data using a series of commands contained in a control file. Again, the flexibility of the program created special problems in allocating RAM space for data storage. Some data sets consist of few variables with lots of observations, and some contain lots of variables and fewer observations. The total number of variables and observations is unknown at compilation time, thus requiring that either a very large fixed data table be allocated or that a dynamic allocation strategy be used. Storage space is allocated for each variable in arrays of 256 slots that are linked together to form a list of data arrays. The slots are 1 byte for binary and categorical variables, 2 bytes for integers, and 8 bytes for real numbers. To maximize use of memory space, eight binary variables are packed into each element of the array (one variable per bit). Thus the use of data packing and dynamic allocation of linked lists of data tables enable SMAS to custom configure the allocation of RAM in a very efficient manner to accommodate many different data base configurations.

Expansion of program size. The bulk of the programming for SMAS involved developing a procedure for each of the analysis commands implemented in the SUMMARY program. This was facilitated by writing a common set of data access routines that are used by all of the procedures. However, as each new procedure was written, the total size of the program grew. One limitation of Turbo Pascal is that the compiled program can be no larger than 64K. This problem was circumvented by using Turbo Pascal's overlay processor. Blocks of memory are allocated at compilation time. The first block contains the main control routine of the program. The other blocks are called overlays, each of which may contain any number of procedures. The amount of space allocated for the overlay corresponds to the amount of space required by the largest procedure. When a procedure in an overlay is called, it is read into memory from the disk. There is a separate disk file of compiled code for each of the overlay blocks. The procedure remains in memory and is executed directly the next time it is called. If a different procedure in the overlay block is called, it is read off the disk replacing the previous procedure in memory. Frequently used routines are not overlaid, utility and memory management routines are kept in separate overlays, and several overlays are allocated for command processor routines.

This process of overlaying procedures allowed for the development of the many analytic procedures presented in Table 1. The extension of SMAS by the addition of new commands is done by adding the new procedures to existing overlay blocks. Thus the program is greatly expandable without ever exceeding the 64K limitation.

Application of SMAS in Behavioral Medicine

SMAS has been used mainly for the assessment and modification of eating behavior in bulimia, hypertension, and obesity. Schlundt, Johnson, and Jarrell (1985) analyzed eating diaries of 8 bulimic and 20 obese patients in order to identify situations that precipitate vomiting, binge eating, and overeating. They found that the environmental control of eating behavior was similar for obese and bulimic subjects in that being alone at home in the evening and being in a negative mood was strongly associated with bingeing and vomiting for the bulimic sample and with overeating for the obese sample. In addition, obese subjects were observed to have significant problems with overeating and excess calorie intake in positive social situations.

Schlundt, Johnson, and Jarrell (1986) used SMAS in conjunction with Markov chain analysis to study sequences of eating episodes in 8 bulimic patients undergoing behavior therapy. In addition to the high-risk situations identified in the Schlundt et al. (1985) study, the sequential data analysis led to the identification of additional behavior patterns. Self-induced vomiting was observed to be highly autocorrelated such that once vomiting occurs at one eating episode, the probability that

vomiting will occur at the subsequent episode is greatly increased. Repeated episodes of vomiting were much more likely to occur when both meals were eaten during the same time period, especially during the evening. In addition, skipping of meals, particularly of breakfast, was associated with a higher probability of vomiting later in the day.

SMAS is potentially useful for the study of any behavior that can easily be self-monitored over time. The process involves first identifying the target behaviors, the environmental and behavioral antecedents, and the potential consequences. These variables are then used to create a self-monitoring diary that subjects are instructed to keep. A file family definition is then created, which translates the diary into a SMAS data base. The diaries are collected, entered into the computer, and SUMMARY is used to generate analytical printouts. These printouts can be used for individual behavioral assessment, as a part of a behavior therapy program, for research purposes, or for program evaluation.

Application of SMAS to Behavioral Assessment in Diabetes

Of the many chronic diseases that afflict people, diabetes involves one of the most complex treatment regimens. The effective management of diabetes involves the control of blood glucose levels through the simultaneous adjustment of insulin injections, food intake, and activity (Unger, 1982). As with most chronic diseases, poor compliance with treatment procedure is a serious problem in diabetes (Sackett, 1976).

In order to better understand and promote patient compliance, psychologists have begun to apply the methods of behavioral medicine to the long-term management of diabetes (Fisher, Delamater, Bertelson, & Kirkley, 1982). Psychologists have become concerned with the social and psychological adjustment of patients with diabetes and with how this affects their medical care (Mazze, Lucido, & Shamon, 1984). The advent of home blood glucose monitoring has led to the widespread use of self-monitoring techniques in diabetes care (Wing et al., 1985). In addition, the use of the self-monitored food intake technique is easily applied to the problem of assessing and modifying compliance with diabetic diets (Pate et al., 1986).

Table 2 presents an example of a self-monitoring diary that we have used with adults diagnosed as having insulin-dependent diabetes mellitus (IDDM). The form is duplicated and made into a booklet that contains enough blank pages for recording a week's worth of meals. Patients are instructed to complete a new page for each meal or snack eaten. The use of multiple-choice formats and rating scales allows the form to be entered directly into the computer with no judgment or interpretation required on the part of the operator. Responses on this diary sample many of the environmental, behavioral, emotional,

Table 2
A Self-Monitoring Diary for Use with IDDM Patients

Time _____ (a.m. p.m.)	Date ____/____
Day (Mo Tu We Th Fr Sa Su)	
Meal (Breakfast Morn-Snack Lunch Aft-Snack Supper Eve-Snack Other)	
Place (Home Work Restaurant Social-Event Car Other)	
People (Family Friend Alone Other)	
Depressed (-- - N + + +)	Happy
Anxious (-- - N + + +)	Calm
Stressed (-- - N + + +)	No Pressure
Tired (-- - N + + +)	Energetic
Hungry (-- - N + + +)	Full
Amount of food eaten (Undereat Just-right Overeat)	
Foods and Beverages Brand Name How Prepared Amount Measured	
_____	Y_ N_
_____	Y_ N_
_____	Y_ N_
_____	Y_ N_
_____	Y_ N_
_____	Y_ N_
_____	Y_ N_
_____	Y_ N_
Any symptoms of low blood sugar since last meal or snack (Yes No)	
Blood Glucose Reading: (Yes No) Value of reading _____	
Exercised since last meal (Yes No) If yes then _____ minutes	
Injection before meal (Yes No)	

and physiological variables associated with each eating episode.

To illustrate the use of SMAS, data are presented from a 17-year-old white female diagnosed as having IDDM who was referred by her physician for dietary compliance counseling. This patient had steadily gained 18 pounds over the past 3 years with no change in height. At the time she was seen, she was 62½ in. tall and weighed 146 lbs. Her glycosolated hemoglobin (HbA_{1c}) was measured at 16.2 at the time of referral, indicating poor glycemic control (Trivelli, Ranney, & Lai, 1971). She had been prescribed a 1,015 Kcal diet about a year ago by the clinic dietitian but experienced no success in following it and losing weight. Her diet prescription was based on the diabetic exchange system and consisted of 245 calories for breakfast, 245 calories for lunch, 315 calories for supper, and an evening snack of 210 calories.

The patient was given the eating diary shown in Table 2 and was instructed to record all meals and snacks until her next appointment. She was told to follow her usual pattern so that an accurate picture of her current eating habits could be obtained. The patient kept the diary for 12 days before returning to the clinic. Each food intake was coded using the diabetic exchange system and entered into the computer using SMAS. The number of servings from each of the six diabetic food groups (meat, milk, bread, vegetables, fruit, and fat) at each meal was entered into the data base, along with information on the context of the eating episode. All but 2 of her 55 eating episodes were reported in sufficient detail to allow for

coding of the nutrient intake. Using QSCORE, the food group servings were used to estimate the grams of protein, carbohydrate, and fat consumed at each meal. Total calories per meal was then computed from the macronutrient content.

Figure 1 presents the average calorie intake by meal. Note that INTCAT also computes and prints the frequency and standard deviation. The reported calorie intakes were quite discrepant from her prescribed meal plan. Her daily calorie intake was averaging over 2,200 calories, with her evening snack alone exceeding her prescription by 319%.

The percent of calories from carbohydrate, protein, and fat was calculated from the SMAS printouts for each meal and is presented in Table 3. This table indicates that the patient was taking in too much fat and too few carbohydrates at all meals except her afternoon snack. It is clear that evening snacking was the most serious problem requiring attention. One of the intervention goals with this patient was to teach her to make dietary substitutions that would help her reduce her overall fat intake and increase her intake of complex carbohydrates. Another goal was to help her make changes in her activity patterns in the

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*****
S M A S - Self-Monitoring Analysis System
Author - David G. Schlundt, Ph.D. (version 3.0)
Date= 2/13/1987 Time= 13:15:32
Analysis of dietary intake for a 17-year old IDDM patient.
Self-monitored situations, food, blood glucose, exercise, and insulin in IDDM
File Family = a:eat Extension = lac
*****
** I N T C A T ** ** I N T C A T ** ** I N T C A T **
Mean values of calories for each category of meal

      0.000  100.000  200.000  300.000  400.000  500.000  600.000
      I****I****I****I****I****I****I****I****I****I****I****I****I
brkfc 448.346 I#####
Sdev  244.137 I#####
freq  13.000 I#####
      I
msnk  0.000 I
Sdev  0.000 I
freq  0.000 I
      I
lunc  497.167 I#####
Sdev  156.852 I#####
freq  12.000 I#####
      I
asnk  167.600 I#####
Sdev  107.625 I#####
freq  5.000 I#####
      I
supr  477.625 I#####
Sdev  155.934 I#####
freq  12.000 I#####
      I
esnk  669.727 I#####
Sdev  232.752 I#####
freq  11.000 I#####
      I
othr  0.000 I
Sdev  0.000 I
freq  0.000 I
      I
miss  0.000 I
Sdev  0.000 I
freq  0.000 I
      I
      I****I****I****I****I****I****I****I****I****I****I****I****I
      0.000  100.000  200.000  300.000  400.000  500.000  600.000

Grand Mean =      485.4906  Number of observations =      53
source      ss      df      ms      F
-----
Between 898961.442      4      224740.361      5.352
Within 2015676.303     48      41993.256

```

Figure 1. Average calorie intake by meal.

Table 3
Percent of Calories from Carbohydrate, Protein, and Fat by Meal

Meal	Source		
	Carbohydrate	Protein	Fat
Breakfast	48	16	36
Lunch	39	19	42
Afternoon Snack	67	12	22
Supper	44	20	36
Evening Snack	37	17	46

evening so as to reduce the frequency and size of evening snacks.

Figure 2 presents the results of running CROSSTAB on the variables depressed by the amount of food eaten (overeating). This patient did not make full use of the response scale on the depression variable, in that she never used the double-negative or double-positive ratings. Examination of the adjusted residuals in this table (z-scores measuring the association between pairs of categories)

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*****
S M A S - Self-Monitoring Analysis System
Author - David G. Schlundt, Ph.D. (version 3.0)
Date= 2/13/198 Time= 13:15:18
Analysis of dietary intake for a 17-year old IDDM patient.
Self-monitored situations, food, blood glucose, exercise, and insulin in IDDM
File Family = a:eat Extension = lac
*****
** C R O S S T A B S ** ** C R O S S T A B S ** ** C R O S S T A B S ** ** C

```

Crosstabulation of (row) depress by (col) overeat

Total number of observations = 53

	undr	jsrt	over	miss	
-	0	0	0	0	0
prob	0.00000	0.00000	0.00000	0.00000	0.00000
P c r	0.00000	0.00000	0.00000	0.00000	
P r c	0.00000	0.00000	0.00000	0.00000	
Z-res	0.00	0.00	0.00	0.00	
-	1	4	8	0	13
prob	0.01887	0.07547	0.15094	0.00000	0.24528
P c r	0.07692	0.30769	0.61538	0.00000	
P r c	0.16667	0.14286	0.57143	0.00000	
Z-res	-0.39	-1.17	2.55	-1.12	
N	2	9	4	3	18
prob	0.03774	0.16981	0.07547	0.05660	0.33962
P c r	0.11111	0.50000	0.22222	0.16667	
P r c	0.33333	0.32143	0.28571	0.60000	
Z-res	-0.03	-0.18	-0.36	1.02	
+	3	14	2	2	21
prob	0.05660	0.26415	0.03774	0.03774	0.39623
P c r	0.14286	0.66667	0.09524	0.09524	
P r c	0.50000	0.50000	0.14286	0.40000	
Z-res	0.41	0.98	-1.59	0.01	
++	0	1	0	0	1
prob	0.00000	0.01887	0.00000	0.00000	0.01887
P c r	0.00000	1.00000	0.00000	0.00000	
P r c	0.00000	0.03571	0.00000	0.00000	
Z-res	-0.34	0.65	-0.52	-0.31	
miss	0	0	0	0	0
prob	0.00000	0.00000	0.00000	0.00000	0.00000
P c r	0.00000	0.00000	0.00000	0.00000	
P r c	0.00000	0.00000	0.00000	0.00000	
Z-res	0.00	0.00	0.00	0.00	
	6	28	14	5	
	0.11321	0.52830	0.26415	0.09434	
Chi-square =		15.041			

Figure 2. Overeating $\times$ depression.

shows that there is a significant association between feeling somewhat depressed and overeating. The conditional probability of overeating given depression is 0.62 as compared with 0.22 for neutral and 0.10 for positive. Examination of the CROSSTAB of meal $\times$ depression showed that negative moods were not associated with any particular meal. There was no significant association between overeating and anxiety, stress, or hunger. To further analyze the impact of overeating, the average calories $\times$ category of overeating was generated. This analysis showed that the mean caloric intake at overeating episodes was 653, compared with 456 for just right and 434 for undereating. An additional therapeutic goal of teaching this patient strategies other than overeating for dealing with depression was identified on the basis of this analysis.

Although hunger was not associated with overeating, it was strongly related to caloric intake. When this patient rated herself as very hungry, she consumed an average of over 900 calories at each meal, compared with 350 calories when she was somewhat full. These results suggest that any intervention strategy employed must enable this patient to avoid becoming very hungry.

Compliance with blood glucose testing was examined. She tested and recorded blood glucose levels for nearly every breakfast and two thirds of her suppers. Her compliance with testing before lunch, however, was poor in that she only tested 25% of the time. The relationship between blood glucose values and hunger ratings was examined using INTCAT. For this patient, lower blood glucose levels were associated with stronger hunger ratings. Her average blood glucose values at breakfast, lunch, and supper were 302, 220, and 305, respectively, all indicating poor control of her diabetes. The high morning value is probably a consequence of her uncontrolled snacking in the evening.

Four goals were initially identified as intervention targets for this patient: reducing the calorie size and fat content of meals, reducing or eliminating overeating in the evening, learning alternative strategies for coping with depression, and lowering premeal blood glucose values. In addition, the patient was warned that as she gains better control over her blood glucose, she may experience increased levels of hunger that may function as a stimulus for overeating. Consequently, this patient was counseled on using lower calorie foods and smaller meals as a way to eliminate hunger without overfeeding herself.

DISCUSSION

The Self-Monitoring Analysis System (SMAS) was presented as a microcomputer application with many potential uses in behavioral medicine. As with many assessment tools, it has seen its first application in a clinical research setting. The use of the system is somewhat expensive in that it requires a microcomputer, the program, and time for coding, entering, and analyzing the data. It does, however, result in a fine-grained analysis

of behavior that would take more than 10 times as long to do by hand. SMAS opens many new possibilities for precision in the field of behavioral assessment, as was illustrated by the case study presented.

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