Development of a Scale to Measure Adherence to Self-Monitoring of Blood Glucose With Latent Variable Measurement

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OBJECTIVE — Adherence to self-monitoring of blood glucose (SMBG) is problematic for many people with diabetes. Self-reports of adherence have been found to be unreliable, and existing paper-and-pencil measures have limitations. This study developed a brief measure of SMBG adherence with good psychometric properties and a useful factor structure that can be used in research and in practice.

RESEARCH DESIGN AND METHODS — A total of 216 adults with diabetes responded to 30 items rated on a 9-point Likert scale that asked about blood monitoring habits. In part I of the study, items were evaluated and retained based on their psychometric properties. The sample was divided into exploratory and confirmatory halves. Using the exploratory half, items with acceptable psychometric properties were subjected to a principal components analysis. In part II of the study, structural equation modeling was used to confirm the component solution with the entire sample. Structural modeling was also used to test the relationship between these components. It was hypothesized that the scale would produce four correlated factors.

RESULTS — Principal components analysis suggested a two-component solution, and confirmatory factor analysis confirmed this solution. The first factor measures the degree to which patients rely on others to help them test and thus was named "social influence." The second component measures the degree to which patients use physical symptoms of blood glucose levels to help them test and thus was named "physical influence." Results of the structural model show that the components are correlated and make up the higher-order latent variable adherence.

CONCLUSIONS — The resulting 15-item scale provides a short, reliable way to assess patient adherence to SMBG. Despite the existence of several aspects of adherence, this study indicates that the construct consists of only two components. This scale is an improvement on previous measures of adherence because of its good psychometric properties, its interpretable factor structure, and its rigorous empirical development.

Management of diabetes is aimed at maintenance of near-normal glucose levels by a strict daily regimen of diet, exercise, and, if necessary, oral medication or insulin injections. Monitoring the regimen's effectiveness is accomplished in part by frequent self-monitoring of blood glucose levels (SMBG). SMBG is used to measure fluctuations of glucose levels in the bloodstream. Results of this monitoring may be used to correct deviations in glucose levels. Although the monitoring does not in itself alter blood glucose levels, it provides the information essential to adjust the regimen and bring glucose levels under control. The Diabetes Control and Complications Trial (1) showed that intensive diabetes management, including frequent SMBG, effectively delays the onset and slows the progression of diabetic complications. Although each patient is typically prescribed an individualized monitoring regimen, in general, the more self-tests performed, the more data professionals and patients have available to make adjustments to the treatment regimen.

Studies have operationalized "adherence" differently, and thus varying rates of adherence have been reported. However, it can be concluded that adherence to SMBG is problematically low. Over the course of a week, 83–88% of patients monitor at some point (2,3). However, only 33–50% monitor daily (4,5). Furthermore, only 32–68% of patients monitor as often as prescribed by their doctor. Diabetes regimens contain all the aspects that make any regimen difficult to comply with. That is, lowest adherence rates occur 1) with patients who have chronic disorders with no immediate discomfort or evident risk; 2) when lifestyle changes are required; 3) when treatment is complex, intrusive, and inconvenient; 4) when behaviors are not directly supervised; and 5) when prevention instead of symptom reduction or cure is the goal (6).

Aspects of adherence

Studies have found that demographics are poor predictors of general diabetes self-care (7–10). More transient variables, however, have been found to relate to adherence. For example, the importance of environmental prompts has been demonstrated in SMBG. Labeling hypodermics with prompts to self-monitor before injections has increased the frequency of SMBG (11). Verbal instructions have also increased diabetes self-care (12) and medication compliance in general (13).

Social factors, such as support from family members or demands made by health care providers, may also affect adherence. Amir et al. (14) found that patient adherence increased as the date of a

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Abbreviations: AASR, average absolute standardized residual; CFI, comparative fit index; SMBG, self-monitoring of blood glucose.

doctor visit approached. The measure for self-monitoring showed high adherence (79%) on the day before a follow-up visit but was only 30% during the 30 days before the visit.

Adherence may also be related to patients' subjective physical assessment of their blood glucose levels. Patient beliefs about bodily cues are very prevalent. However, the strength of the patients' beliefs is not predictive of the accuracy of the beliefs, and most patients adhere to at least one false belief (15,16). There is great variability in patients' ability to predict their glucose levels accurately (15–18). Even when patients are relatively accurate in their predictions (e.g., a correlation of 0.70), this accuracy does not generalize to extremes of blood glucose. That is, as blood sugars get higher and lower, accuracy gets worse (19). Patient estimation errors are most commonly in the direction of perceiving the blood glucose concentration as normal when it was either abnormally high or low (17,18,20). Also, there is a general trend for patients to be less adherent with medical regimens when they are in physical distress (21). Thus, when patients are feeling poorly due to hypo- or hyperglycemia, they may not feel well enough to monitor, but this is precisely when they need to monitor to make treatment decisions.

Patients' expectations of results may inhibit monitoring. Results outside of the normal range can be interpreted as failure on the part of patients. Consequently, patients may be more likely to monitor on days when they feel that their blood glucose level is normal and expect normal results. Rothbaum et al. (22) found that ignoring or reporting symptoms is related to other than strictly metabolic factors, in particular factors having to do with self-concept. Additionally, self-esteem is associated with metabolic balance (23).

Thus, adherence has been thought to incorporate frequency and timing of tests and reliability of self-reports. Several variables have been associated with general diabetes self-care, namely, social factors and prompts. It also appears that other variables might be related to adherence, namely reliance on bodily cues and expectation of results.

Measurement of adherence

An important aspect of adherence is the reliability of patient self-reports. To assess this, several studies have measured the reliability of logbooks to the corresponding results retrieved from reflectance photometers with a memory function. Mazze et al. (24) found inconsistencies in both the reported occurrences of the monitors, and the result of the monitors. Other studies have also found inconsistencies (25,26). Wing et al. (3) found that SMBG frequency, duration, and accuracy were unrelated to each other. Although accurate in terms of memory, reflectance photometers provide no insight into the set of conditions that lead to nonadherence. There are many reasons that a patient may not be monitoring. There is the possibility that patients have not been prescribed a monitoring regimen. Ruggiero et al. (27) found that of 2,056 diabetes patients sampled, only slightly more than half of the individuals with NIDDM not taking insulin were reportedly given any recommendations to self-monitor. It could be argued that this information is based on self-report and may reflect a recall problem. However, it is just as problematic if individuals do not recall recommendations or do not have a clear understanding of the recommendations, because they will be unlikely to perform the self-care tasks needed. There is also the possibility that patients have been instructed to self-monitor but have not been properly educated to use the results to make necessary changes. Without this key understanding, patients are not likely to see the benefit of self-monitoring and may do so less frequently. Another reason patients may not self-monitor is because the blood glucose results can become punishing. Although the blood glucose level is simply data, it can become negative feedback to patients who interpret high and low blood glucose results as failure and feel frustrated, guilty, or demoralized. On the other hand, patients may choose not to test because they are feeling fine and therefore do not see the need to test. The existing measures of adherence do not capture these more subtle, yet important, aspects of adherence.

One reason for the unreliability of self-reports may be that adherence is often measured by a single item, for example, "Do you regularly follow your blood testing regimen as prescribed by your doctor?" A more sophisticated approach to self-report is latent variable measurement. A latent variable is the underlying phenomenon, or construct, that a scale is intended to reflect. In this case, the latent variable is adherence. A latent variable cannot be directly observed or quantified. It can only be estimated from items that are written to tap into it. These observable items are referred to as manifest variables.

There is an implicit relationship between latent and manifest variables (28). The latent variable is regarded as a cause of the manifest variable, that is, the amount of adherence presumably causes an item on the scale to take on a certain value. This value varies under different conditions. For example, adherence may vary as a function of the existence of prompts, symptomatology, and social factors. A set of items that are caused by the same latent variable can be examined in concert. With several items that measure adherence, we can look directly at how they correlate with one another, invoke the latent variable as the basis for the correlations among the items, and use that information to infer how highly each item is correlated with the latent variable. Latent variable measurement is a well-regarded schema for understanding the relationship between measures and the constructs they represent.

With principal components analysis, we can examine the number of latent variables, or components, that a set of items taps. For example, we can determine whether there really are four latent variables (prompts, social factors, symptomatology, and accuracy) that make up the higher-order latent variable adherence or whether these seemingly different latent variables form any number of underlying components. Further, with structural equation modeling, we can confirm the number of components and examine the relationship between several latent variables. For example, are the underlying components correlated with each other or not? The schema of latent variable measurement, combined with the powerful techniques of structural equation modeling, allows researchers to gain a much fuller understanding of complex phenomena such as adherence.

In light of the body of research on adherence and the approach of latent variable measurement, the present study sought to answer the following questions. *1*) What are the psychometric properties of this scale? It was predicted that the scale would produce adequate internal consistency. *2*) Does each aspect of adherence form its own component, or does adherence have a more parsimonious underlying factor structure? It was predicted that a four-component solution would emerge, with one component representing each aspect of adherence. It was specifically hypothesized that use of symptomatology

would emerge as an aspect of adherence. *3*) How do these factors relate to each other? It was predicted that these factors would be correlated to each other.

RESEARCH DESIGN AND METHODS

— For the present study, 216 adults diagnosed with diabetes were recruited. The population from which the sample was drawn were patients who participated in the diabetes education program offered by the hospital (n = 2,252). The population consisted of mostly non-insulin-dependent (92%) adults (87% were over 41 years old); 52% were male, 48% were female. Most were white (85%) or Hispanic (14%), with fewer than 1% African-American, Asian American, or Native American. Patients recruited were representative of the larger hospital diabetes population.

Procedure

Questionnaires were mailed to approximately 1,000 potential participants, along with informed consent forms and a postage-paid return envelope. Two hundred sixteen (216) participants replied, yielding a 22% return rate. There was no incentive for participation.

Participants responded to 30 items measured on a 9-point Likert scale (1 = lower adherence, 9 = greater adherence) that asked about blood monitoring habits. Items were formulated from several sources. First, items were written to measure the three known aspects that have emerged in the literature (use of prompts, social factors, and accuracy). Second, items were written to measure blood glucose symptomatology to test its relationship to adherence. Finally, items were carefully reviewed and edited by colleagues in the field of health care compliance, some of whom also had diabetes themselves.

Three analyses were conducted in part I of the present study. First, the distributional assumptions (i.e., normality) of each item were examined, and the items showing extreme nonnormality (i.e., skewness >4 or kurtosis >2) were eliminated from subsequent analysis. Second, to explore the component structure underlying the remaining 23 items, data from half of the sample (randomly chosen) was examined using a principal components analysis with an oblique rotation. The principal components analysis was conducted using the CAX (Components Analysis Extended) software package (29). This software was selected because it provides reliable statistical criteria for identifying the number of components within a set of measured variables. Finally, the reliability of the components was examined using Cronbach's α (30) as an indicator of internal consistency, with values >0.75 considered reliable.

In part II of the present study, confirmatory factor analysis was conducted using structural equation modeling procedures. With EQS software (31), we confirmed the component structure identified in part I using the entire study sample. Structural equation modeling is a statistical procedure designed to assess the ways in which a set of constructs (latent and/or manifest) relate to one another in a multivariate framework. One benefit of structural equation modeling includes the ability to examine how a set of measured variables relate to a single latent construct and conduct confirmatory factor analytic tests (32).

In its simplest form, a model that depicts how the set of variables relate to one another is proposed; then, based on the model's variance-covariance structure, the model is compared with the "actual" variance-covariance structures in the observed data. The degree to which the model's variance-covariance structure overlaps with the variance-covariance structure in the observed data determines whether the model "fits" the data and therefore can be accepted as one potential model of these interrelationships (33).

However, rarely is structural equation modeling used to evaluate a single model. Rather, ideally, several models should be evaluated (often based on differing theoretical formulations) and compared with one another to identify the model that fits best. The goodness of fit between a proposed and observed model is determined using three criteria: *1*) theoretical consistency, *2*) empirical evidence, and *3*) parsimony (34).

Empirical evidence concerns statistical evaluation of the respective models. A widely used omnibus model fit index is the χ^2 test, where model fit is indicated when there is a failure to reject the null hypothesis (i.e., probability values >0.05) and when the ratio of χ^2 to the degrees of freedom (df) for the model is <2.0. In addition, adjunctive fit indexes have been constructed as indexes of the degree of variation and covariation in the observed data that is accounted for by the specified model. The comparative fit index (CFI) represents the degree of shared variation between model and data (greater accounted variation when values approach 1.00) (35). The average absolute standardized residual (AASR) represents the average difference between the sample variances and covariances and the estimated population variances and covariances (values approaching zero when the model is increasingly accounting for variation) (34). The CFI and the AASR are well-established and recommended fit indexes (35). Conventionally, CFI values >0.90 and AASR values ≤0.06 indicate good model fit. Finally, in addition to fit indexes, a model is examined in terms of the significance of specific parameters linking constructs using z-ratios (i.e., factor loadings, regression coefficients) and explained variance estimates (R^2) for variables within the model. When models are no different in terms of their empirical comparison, the model that shows greater theoretical consistency and greater parsimony is considered to be superior (L. Harlow, J. Rose, unpublished observations).

Because of the relatively small size of the confirmatory half of the sample (n = 108), two separate models were tested on the entire sample, using the maximum likelihood estimation procedure. Structural equation modeling procedures, used in this fashion, were intended to replicate (i.e., confirm) the same component structure that was identified in part I of the present study. The confirmatory models were as follows: model 1, the correlated model, depicted the component structure identified in part I of the present study and assumed that the components were correlated, but without the existence of a higher-order component; and model 2, the uncorrelated model, depicted the component structure identified in part I of the present study and assumed that the components were uncorrelated.

RESULTS

Part I: assessment of normality and the determination of the component structure

Table 1 shows the descriptive statistics calculated for the 30 questionnaire items to examine the normality assumption. As can be seen, several items showed extreme "floor effects" (i.e., item responses were piled up at the extreme low end of the response scale) as evidenced by the mean values of approximately 1.00 and extreme kurtosis and skewness values. Values for skewness and kurtosis should be approximately zero if the distribution is normal. Although there are no

Table 1—*Descriptive statistics for 30-item scale (n = 216) and component loadings after rotation for 23 items (n = 108)*

Item	Item description	Means ± SD	Kurtosis	Skewness	Physical influence	Social influence
Q1	If I feel my blood sugar is low . . .	3.18 ± 2.55	−0.14	0.94	0.45*	0.32
Q7	When I am sick, I test . . .	3.60 ± 2.33	−0.41	0.48	0.62*	0.21
Q18	Someone asks and I haven't tested . . .	3.91 ± 3.26	−1.28	1.27	0.62*	0.22
Q19	If at work and I am low . . .	4.20 ± 2.39	−0.49	0.06	0.51*	0.05
Q20	When tempted to eat sweets . . .	5.91 ± 3.34	−1.33	−0.52	0.47*	0.32
Q25	If at a party, I feel hypoglycemic . . .	5.12 ± 3.18	−1.23	−0.24	0.67*	0.26
Q28	If I feel high, I test . . .	2.72 ± 2.28	0.24	1.04	0.50*	0.11
Q29	If I feel low, I test before eating . . .	4.31 ± 3.31	−1.52	0.23	0.59*	0.24
Q3	After I test my blood glucose . . .	2.79 ± 2.94	−0.08	1.26	0.35	0.54*
Q5	I test my blood when . . .	3.29 ± 2.46	3.45	2.05	0.30	0.75*
Q10	If none checked, I would . . .	2.09 ± 2.11	3.45	2.05	0.25	0.82*
Q11	When it is time to test, someone . . .	2.33 ± 2.39	1.44	1.61	0.11	0.70*
Q23	I record my results when . . .	2.94 ± 2.73	0.09	1.15	0.33	0.67*
Q24	If no one told me to test . . .	2.37 ± 2.46	1.50	1.65	0.31	0.80*
Q30	I need someone to remind me . . .	1.87 ± 2.33	3.86	2.24	0.24	0.72*
Q2†	When it is time to test, I . . .	4.48 ± 2.73	−1.05	0.26	0.48	0.69
Q8†	If I'm at work . . .	4.73 ± 3.35	−1.33	−0.20	0.51	0.40
Q13†	If I'm at a party . . .	6.02 ± 3.04	−0.72	−0.68	0.54	0.48
Q14†	My doctor tells me I test . . .	4.69 ± 2.47	−0.14	−0.23	0.51	0.63
Q16†	I test __% of the time . . .	2.52 ± 2.35	0.93	1.37	0.50	0.83
Q17†	When someone at home asks . . .	4.76 ± 3.92	−1.90	0.03	0.07	0.02
Q22†	When it is time to test . . .	2.47 ± 2.49	1.24	1.56	0.51	0.90
Q26†	My doctor tells me I record my results . . .	4.75 ± 2.48	−0.13	−0.28	0.49	0.65
Q4‡	After I test my blood glucose . . .	1.30 ± 1.13	23.37	4.48	—	—
Q6‡	When I know that my doctor will ask . . .	1.40 ± 1.54	8.24	2.64	—	—
Q9‡	I ___ wipe alcohol on the strip . . .	1.00 ± 1.01	52.59	6.80	—	—
Q12‡	When I record my results . . .	1.19 ± 0.88	43.13	6.10	—	—

*Significant loading on respective component; †item deleted because of poor loading; ‡item deleted due to skewness/kurtosis.

reliable procedures for determining whether these values represent nonnormality (37), the extreme values of certain items in the present study (9.92–87.75) clearly indicates that they have nonnormal distributions and should, thus, be eliminated. Consequently, seven items were eliminated (Q4, Q6, Q9, Q12, Q15, Q21, and Q27).

Figure 1 shows the component loadings after an oblique rotation. An oblique rotation—as opposed to an orthogonal rotation—was used because it was thought that the components would be correlated. Both the maximum average partial (MAP) and the parallel analysis (PA) rules for determining the number of components indicated that there were two components underlying the 23 items. Whether individual items could be considered part of a specific component was determined by the component loading after rotation. Tabachnick and Fidell (37) and others consider an item to be part of a component if the loading is ≥0.40 (i.e., 16% of the variance) and the item does not load highly on any other component (i.e., complex loading).

Component 1, labeled social influence, appeared to measure external or social influence on blood glucose monitoring and accounted for 27.92% of the variance among the 23 items. Component 2, labeled physical influence, appeared to measure internal or physical influence on blood glucose monitoring and accounted for 15.31% of the variance among the 23 items. The analysis indicated that seven items measured social influence and eight items measured physical influence. The remaining eight items were either complex (i.e., loaded on both components) or failed to load on either component and were therefore deleted from subsequent analyses (Q2, Q8, Q13, Q14, Q16, Q17, Q22, and Q26).

Finally, each of the subscales as well as the entire scale showed adequate internal consistency reliability. The estimates of internal consistency using Cronbach's α were 0.84 (total scale), 0.85 (social influence), and 0.74 (physical influence).

Part II: structural equation modeling

Using the entire sample, structural modeling was used to confirm the component structure delineated in part I of the present study. As stated above, the two models examined were model 1, the correlated model, and model 2, the uncorrelated model. The correlated model has some theoretical support and adequate parsimony and received equally strong empirical support compared with the higher-order model. Again, all component loadings were significant ($P < 0.05$). Further, the ratio of χ^2 to degree of freedom, the CFI, and the AASR all indicated good model fit (χ^2 [89] = 129.56, $P < 0.001$; CFI = 0.91; AASR = 0.05]. These findings indicate that a very small degree of variation remains unexplained and are empirically identical to the findings of the higher-order model.

In contrast, the uncorrelated model, although showing some grounding in theory, and adequate parsimony, received less than adequate empirical support. Although all component loadings were significant ($P < 0.05$), confirming the component structure, model fit criteria were below acceptable levels (χ^2 [90] = 154.62, $P < 0.001$;

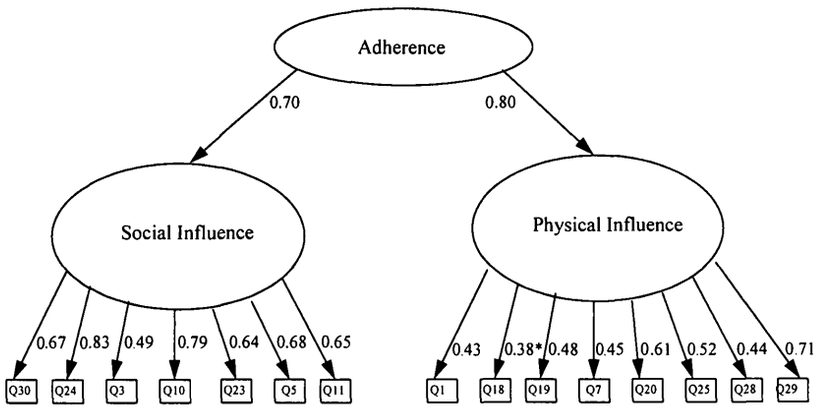

Figure 1—*The higher-order model. Note: parameters significant at* $P < 0.001$; *$P < 0.01$, all other loadings significant at $P < 0.001$; $\chi^2 (89) = 129.56$; CFI = 0.91; AASR = 0.05.*

ASSR = 0.12; CFI = 0.86). These findings suggest that a substantial degree of variation and covariation present in the data is not accounted for by this proposed model. A χ^2 difference test indicates a significant difference between the fit of the uncorrelated model and the correlated models $\chi^2_{diff}(1) = 25.06$, $P < 0.001$, favoring the correlated models.

CONCLUSIONS — In this study, latent variable measurement was used to assess adherence to SMBG. In part I of the study, seven items were deleted due to extreme nonnormality. These items tended to ask about "cheating" during monitoring; for example, reporting that a test was performed when in fact it was not or lying about the results of a test. These items were endorsed so infrequently that they were deleted from the scale. This finding is in contrast to some literature on self-report that found that respondents overreport the frequency with which they monitor and alter the results of monitors. There are several possible explanations for this finding. First, it is possible that the respondents to this survey differed in a systematic way from diabetes patients who have been studied in the past. Because there was no incentive to participate, the subjects who did respond may have been more concerned about or interested in their diabetes treatment than average patients and therefore also less likely to overreport. Second, it is possible that the respondents were not forthcoming with their true self-testing habits. Without any further validation of this scale, it is impossible to know whether the participants were truthful, or whether they did not endorse items that in fact applied to them. This seems unlikely, as the survey was completely anonymous and was clearly for research, rather than clinical, purposes. Third, it is possible that past methods of measuring adherence inflated rates of overreporting. Adherence is often studied in nonadherent populations, because it is this population that needs intervention. By deliberately studying nonadherent patients, diabetes researchers may have selected a biased population. It is possible that diabetes patients in general do not overreport their self-testing rates or change their results. Fourth, it is possible that there was a difference between responders and nonresponders. Return rate was low (22%), and participants who responded to the survey may be systematically more adherent than those who did not respond.

Once these 7 items were deleted, the resulting 23 items were analyzed to determine the number of components they formed. It was hypothesized that each of the four aspects of adherence would form separate components. This hypothesis was not supported. The scale formed just two components. One component tapped social determinants of a patient's likelihood of testing and thus was named social influence. A typical item on this component asks whether a patient relies on family members to remind them to test. The other component tapped physical determinants of a patient's likelihood of testing and thus was named physical influence. A typical item on this component asks whether a patient is more likely to test if experiencing symptoms of hypoglycemia. This second component is a significant addition to the literature, as it has been assumed, though not confirmed, that symptomatology plays a role in adherence. Of the 23 items, 8 did not load appropriately on either component and were therefore deleted.

The remaining 15 items were assessed for their psychometric properties. It was hypothesized that they would be reliable. This hypothesis was confirmed, and the scale shows adequate reliability.

Next, these items were analyzed with the entire sample to confirm the two-component structure. This structure was confirmed with a good fit of the data. It was hypothesized that the components would be correlated. This hypothesis was confirmed. Results indicate that the two components are correlated. This correlated model implies existence of a higher-order latent variable that subsumes "social influence" and "physical influence." This higher-order construct is presumed to be adherence. The correlated and higher-order models are mathematically equivalent, so there is no empirical evidence to choose the higher-order model over the correlated model. Both fit the data equally well. However, for theoretical considerations, the higher-order model is viewed as the best model. The existence of a correlation between the latent variables of physical influence and social influence implies a higher-order factor.

These components have implications for understanding and addressing adherence issues in patients. For example, patients who rely heavily on symptomatology as a cue to test are probably not following a testing schedule but simply testing whenever they experience blood glucose symptomatology. It is important for this type of patient to know about the unreliability of symptomatology and the importance of a daily testing routine. Also, patients who only test when they feel that they are outside of the normal range are never reinforced for testing by getting normal results. If continually faced with high and low blood glucose results, patients may become demoralized and test less frequently. Thus, it is important that patients also test when they feel normal so that they can be reinforced for testing at all. On the other hand, if patients rely heavily on social cues to test, it is important to discover whether those cues are available. For example, are these patients in fact reminded to self-test by a family member? If so, and the family is comfortable with this arrangement, then no intervention is necessary. If, however, patients are waiting for cues that are not forthcoming, their family could be urged to help or patients could be coached to establish their own cues for test-

ing. For example, they could be instructed to pair testing with other daily routines, such as brushing teeth before bed or reading the morning paper.

The development of this scale has produced a 15-item, psychometrically sound measure of SMBG adherence. Its two-factor structure makes it an interpretable, potentially useful scale for both research and clinical work. Because it is brief, it could be easily administered during office visits, supplying health care professionals with data as to how best intervene with nonadherent patients. Because of its rigorous empirical development, researchers can use it knowing that it has good reliability and initial indicators of factorial validity.

Future directions should first be aimed at replicating these results with different samples. Any differences between responders and nonresponders could then be examined systematically. This would allow researchers to address the question of overreporting. That is, is it common for all patients to overreport, or is this a behavior limited to generally nonadherent patients? Second, efforts should be made to further validate this scale. For example, scores on this scale could be compared with reflectance photometer memories or other established measures of adherence. This type of research can yield a better theoretical understanding of adherence and create better interventions to improve the health and lives of our patients.

References

1. Diabetes Control and Complications Trial: The effect of intensive treatment of diabetes on the development and progression of long-term complications in insulin-dependent diabetes mellitus. *N Engl J Med* 329:977–986, 1993
2. Gonder-Frederick L, Julian D, Cox D, Clarke W, Carter W: Self-measurement of blood glucose: accuracy of self-reported data and adherence to recommended regimen. *Diabetes Care* 11:579–585, 1988
3. Wing R, Epstein L, Nowalk M, Scott N, Koeske R: Compliance to self-monitoring of blood glucose: a marked item technique compared with self-report. *Diabetes Care* 8:456–460, 1985
4. American Diabetes Association: *1993 Diabetes Vital Statistics*. Alexandria, VA, American Diabetes Association, 1993
5. Guthrie D: Interventions for clients with diabetes mellitus. In *Medical-Surgical Nursing*. Ignatavicius D, Bayne M, Eds. Philadelphia, WB Saunders, 1991
6. Rodin J, Salovey P: Health psychology. *Annu Rev Psychol* 40:533–579, 1989
7. Wysocki T, Hough B, Ward K, Green L: Diabetes mellitus in the transition to adulthood: adjustment, self-care, and health status. *Dev Behav Pediatr* 13:194–201, 1992
8. Kavanaugh D, Gooley S, Wilson P: Prediction of adherence and control in diabetes. *J Behav Med* 16:509–522, 1992
9. Goodall T, Halford W: Self-management of diabetes mellitus: a critical review. *Health Psychol* 10:1–8, 1991
10. Russell M (Ed.): *Behavioral Counseling in Medicine*. New York, Oxford University Press, 1986
11. Wagner J, Gipson M: Improving adherence to diabetes blood glucose monitoring regimens with prompts and unit dose packaging. *Behav Therapist*. In press
12. Heiby E, Gafarian C, McCann S: Situational and behavioral correlates of compliance to a diabetic regimen. *J Compliance Health Care* 4:101–116, 1989
13. Demetral D, Gispon M, Irvin W, Anderson W, Catania P: Improving compliance with psychiatric medication regimens using prompts and reinforcements. *Behav Therapist* 4:19–20, 1981
14. Amir S, Rabin C, Galatzer A: Cognitive and behavioral determinants of compliance in diabetics. *Health Soc Work* 144–151, 1990
15. Cox D, Clarke W, Pohl S, Gonder-Frederick L, Hoover C, Zimbelman L, Pennebaker J: Accuracy perceiving blood glucose in IDDM patients. *Diabetes Care* 8:529–536, 1985
16. Gonder-Frederick L, Cox D, Bobbitt S, Pennebaker J: Blood glucose symptom beliefs of diabetic patients: accuracy and implications. *Health Psychol* 5:327–341, 1986
17. Freund A, Bennett-Johnson S, Rosebloom A, Alexander B, Apperson H: Subjective symptom blood glucose estimation, and blood glucose concentrations in adolescents with diabetes. *Diabetes Care* 9:236–243, 1986
18. Wing R, Epstein L, Lamparski D, Hagg S, Nowalk M, Scott N: Accuracy in estimating fasting blood glucose levels by patients with diabetes. *Diabetes Care* 8:214–218, 1984
19. Schandry R, Leopold C, Vogt M: Symptom reporting in asthma patients and insulin dependent diabetics. *Biol Psychol* 42:231–244, 1996
20. Cox D, Gonder-Frederick L, Julian D, Cryer P, Herrman L, Richards F, Clarke W: Intensive versus standard blood glucose awareness training (BOAT) with insulin-dependent diabetes: mechanisms and ancillary effects. *Psychosom Med* 53:453–462, 1991
21. Sherbourne C, Hays R, Ordway L, DiMatteo M, Kravitz R: Antecedents of adherence to medical recommendations: results from the Medical Outcomes Study. *J Behav Med* 15:447–468, 1992
22. Rothbaum P, Salas M, Heiss W: Health assessments of youngsters with insulin dependent diabetes. *J Pediatr Psychol* 17:215–229, 1990
23. Viinamaki H, Niskanen L, Korhonen T, Tahka V: The patient doctor relationship and metabolic control in patients with type I (insulin dependent) diabetes mellitus. *Int J Psychiatry Med* 23:265–274, 1993
24. Mazze R, Shamoon H, Pasmantier R, Lucido D, Muirphy J, Hartmann K, Kuyendall V, Lopatin W: Reliability of blood glucose monitoring by patients with diabetes mellitus. *Am J Med* 77:211–217, 1984
25. Langer O, Mazze R: Diabetes in pregnancy: evaluating self monitoring performance and glucoemic control with memory-based reflectance meters *Am J Obstet Gynecol* 155:635–637, 1986
26. Wilson D, Endres R: Compliance with blood glucose monitoring in children with type 1 diabetes mellitus. *J Pediatr* 108:1022–1024, 1986
27. Ruggiero L, Glasgow R, Dryfoos J, Rossi J, Prochaska J, Orleans T, Prokhov A, Rossi S, Greene G, Reed G, Kelly K, Chobanian L, Johnson S: Diabetes self-management: self-reported recommendations and patterns in a large population. *Diabetes Care* 20:568–576, 1997
28. DeVellis, R: *Scale Development*. Newbury Park, CA, Sage, 1991
29. Velicer W, Fava J, Zwick W, Harrop J: *CAX: Component analysis extended, a computer program*. Kingston, RI, University of Rhode Island, 1988
30. Cronbach L: Coefficient alpha and the internal structure of tests. *Psychometrika* 16:297–334, 1951
31. Bentler P: *EQS Structural Equation Program Manual*. Los Angeles, CA, BMDP Statistical Software, 1995
32. Hoyle R (Ed.): *Structural Equation Modeling: Concepts, Issues, and Applications*. Thousand Oaks, CA, Sage, 1995
33. MacCallum R: Model specification: procedures, strategies, and related issues. In *Structural Equation Modeling: Concepts, Issues, and Applications*. Hoyle R, Ed. Thousand Oaks, CA, Sage, 1995, p. 16–36
35. Hu L, Bentler P: Evaluating model fit. In *Structural Equation Modeling: Concepts, Issues, and Applications*. Hoyle R, Ed. Thousand Oaks, CA, Sage, 1995, p. 76–99
36. Bentler P: Comparative fit indices in structural models. *Psychol Bull* 11:238–246, 1990
37. Tabachnick B, Fidell L: *Using Multivariate Statistics*. 2nd ed. New York, HarperCollins, 1989