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Soft Modeling and Special Education

STEVEN PULOS AND NEAL ROGNESS

ABSTRACT

THIS ARTICLE BRIEFLY DESCRIBES SOFT MODELING WITH PARTIAL LEAST SQUARES (PLS) IN A NONTECHNICAL MANNER. SOFT MODELING WITH PLS WAS DEVELOPED BY HERMAN WOLD (1985) FOR MODEL BUILDING AND EVALUATION IN SITUATIONS WITH HIGH COMPLEXITY BUT WITHOUT WELL-ARTICULATED THEORIES. BECAUSE MANY BELIEVE THAT THIS IS THE SITUATION IN EDUCATION, WE BELIEVE THAT SOFT MODELING WITH PLS IS A USEFUL TOOL FOR EDUCATIONAL RESEARCH.

THE WORLD OF CHILDREN IS EXCEEDINGLY COMPLEX. Not only is there complexity in their cognitive, social, and personality development, but also in the social structures (e.g., families, schools) they live in, which are in turn embedded in other complex social systems (Bronfenbrenner, 1989). In spite of this complexity, professionals in the helping and teaching professions are called upon to make major decisions that affect the lives of individual children. Providing information that can assist decision makers is a primary goal of educational and developmental research. In this article we present a methodology, Soft Modeling, which we believe can be of great assistance in this process.

Soft Modeling helps us to construct and evaluate models of how children learn and develop. Unlike other modeling methods, Soft Modeling is ideally suited for very complex systems when there is a relative lack of theoretical knowledge. The method of Soft Modeling is so named because hard theoretical knowledge is not required for

model building. (A brief comparison of Hard and Soft Modeling is presented toward the end of this article).

The desired result of Soft Modeling is a model that allows us to make better predictions than we could without the model. It does not assume that we have identified causal relations or that we have a "true" picture of the relations among a set of variables. It merely provides us with a model that can lead to better predictions. The value of models is that they do not provide us with isolated pieces of information, but rather with a map of how the system functions. Models contain both the entities that affect the outcome of concern and a description of how the entities influence both each other and the outcome. This latter aspect of models is especially important, because without it we cannot separate indirect, direct, and spurious effects.

The goal of this article is to present a brief overview of Soft Modeling, along with its benefits, so that special education researchers may decide whether or not it might be useful to them. It is aimed at the reader with little or no background in advanced statistics and avoids detailed mathematical and conceptual descriptions of Soft Modeling. If the reader is interested, other sources are readily available to provide (a) an excellent and detailed manual for conducting and reporting a Soft Modeling analysis (Falk & Miller, 1993), (b) conceptual explanations and examples (Ketterlinus, Bookstein, Sampson, & Lamb, 1989; Lohmoller, 1982; Noonan & Wold, 1983, 1985; Noonan, 1989; Sellin, 1986), (c) mathematical explanations (Lohmoller, 1985; Wold, 1981, 1985), (d) philosophical and theoretical implications and background (Dagum, 1989; Wold, 1989), (e) extension and elaborations of Soft Modeling (Falk & Miller, 1991; Lohmoller & Wold, 1984).

A SOFT MODELING WORLDVIEW

Although most research methods may be used within different worldviews, they may match some better than others. In this section we will offer a worldview consistent with the Soft Modeling framework, focusing on the natures of reality, society, and knowers.

Reality

The view of reality most consistent with Soft Modeling cannot be described any better than the quotation from Thom (1975) as it appears in Dagum (1989, p. 124): "Whatever is the ultimate nature of reality (assuming that this expression has meaning), it is indisputable that our universe is not chaos. We perceive beings, objects, and things to which we give names. These beings or things are forms or structures endowed with a degree of stability; they take up some part of space and last for some period of time." As we will soon see, knowledge consists of constructing a model that matches the invariants we encounter in this "reality." It is not necessary to make any hard assumptions about this reality, as do materialists and radical constructivists.

Society

A view implicit in many applications of Soft Modeling is that society is exceedingly complex, poorly understood, and may never exist as a closed system. If society were simple and well understood, there would be no need for Soft Modeling, and traditional Hard Modeling (modeling based upon the maximum likelihood method, e.g., LISREL) would be satisfactory. If we accept this complex view of society, and there is little evidence to the contrary, we have two alternatives: First, we may use traditional methods that grossly oversimplify our representation of society. However, we cannot understand a complex system, such as society, by studying the parts in isolation. The separate pieces do not reveal their own interrelations. Furthermore, when the representation of society is simplified, we cannot use sophisticated modeling procedures. Inherent in most Hard Modeling is the assumption of a closed system (all relevant aspects of the phenomenon are reflected in the model). If important variables are left out of the model, we have a biased result. Hard modeling also makes strong assumptions about the mathematical properties of the variables we use to study the system. When the system is poorly understood, however, the assumptions may be unwarranted. As a second alternative, we may adopt a method that can handle great complexity and/or systems that are poorly understood from the beginning. This is the situation Soft Modeling was designed to handle. There are other methods that could perhaps handle this situation

(e.g., models based upon Fuzzy System Theory), but they have yet not been applied to developmental and educational questions.

The Knower

Soft Modeling is frequently associated with a philosophy of science known as Theoretical Empiricism (Wold, 1989). This position is consistent with the view that humans acquire knowledge neither solely by indication (abstracting knowledge exclusively from observations) nor solely by deduction (a priori cognitive constructions). Instead, knowledge is constructed from a dialectic between induction and deduction (i.e., between observed data and constructed theory). Theoretical empiricism follows both the classical tradition of Aristotle and Thomas Aquinas and the contemporary philosophy of science (Dagum, 1989).

Several important implications for research stem from this perspective. First, given that knowledge construction stems from this interaction between theory and observation, the traditional notion of a crisp distinction between exploratory and confirmatory data analysis disappears into a fuzzy continuum. In the course of knowledge acquisition, the theory becomes a better match to the data. The theory becomes simpler and extends to more variables (Lohmoller, 1989). A method like Soft Modeling is desirable because it allows one to test the evolving model. Second, given that knowledge acquisition represents both cognitive and empirical entities, the method of analysis must be able to contain both types of entities and specify the relations among them. This is accomplished in Soft Modeling through explicit connection between manifest and latent variables.

Theoretical Empiricism is in stark contrast with positivism, which emphasizes the separateness of theory and observation and the role of operationalism. In Theoretical Empiricism, observation and theory develop together and are evaluated by how well they match each other in a specific context. Further, variables need not be operationally defined; rather, they are defined by their relations to other constructs (i.e., by their nomological network) (Cronbach & Meehl, 1956).

THE FOCUS AND NATURE OF SOFT MODELING

Soft Modeling is conducted with a mathematical procedure known as Partial Least Squares (PLS) (Wold, 1969, 1985). Perhaps the easiest way to understand what Soft Modeling is about is to trace the steps used in the process of Soft Modeling. The steps in conducting a study using Soft Modeling are outlined below, along with a hypothetical example. Our discussion draws heavily from the ISEER model (Falk & Miller, 1991) and the steps outlined by Lohmoller (1989).

All useful modeling starts with a problem to solve and some hunches about how to solve it. In our hypothetical example, consider a researcher who would like to increase the reading capabilities of students with reading difficulties and believes that whole language instruction may be effective. Further suppose that the researcher is interested in studying the effect of whole language instruction in a real world context in order to increase the external validity of the study.

Step 1—Selecting Latent Variables

As a starting point to any study, investigators ask themselves what variables may be relevant to the research question. These variables may come from an explicit theory, previous research, or hunches from an implicit theory. At this point the variables are conceptual entities and not variables to be measured directly. Such variables are termed *latent variables* (LVs). For instance, in this step we could be interested in the latent variable of reading ability without being concerned with how we will actually measure it. PLS allows us to use many more LVs than most hard modeling procedures, which is a real benefit in that important variables are less likely to be missing. This advantage is particularly important at the initial phase of our research when we may have hypothesized many LVs. We should, however, keep the number of LVs less than the number of participants in the study (Falk & Miller, 1993).

In our example, the researchers may decide that whole language instruction may be influenced by contextual variables. Perhaps they have observed that certain teachers who use whole language have a different overall teaching style, and they think this may influence the use of whole language, or may even be the basis of the student improvement associated with whole language instruction. They may also have read how the pupil's attitude and the school climate can influence teaching style. Let's suppose the researcher has identified the following school-related variables that might influence reading ability: (a) use of whole language instruction, (b) general teaching style, (c) school climate, (d) classroom environment, (e) the pupils' attitude toward reading, and (f) the administrative structure of the school. Of course, in the real world we would probably include far more variables, but for the sake of illustration we are keeping the model simple.

Step 2—Specifying the Inner Model

The investigator must now specify how the LVs are related to one another. This description is termed the *inner model*. Usually the model is expressed as a diagram, with some kind of shape—a circle or a square, for example—representing the LVs and the lines between them representing the relations among them. The direction of influence is represented by an arrow. At the current time there is not a standard for drawing the diagram, though the RAM sys-

tem (see Falk & Miller, 1993, for PLS applications) may be the most useful. Even if one does not choose to use Soft Modeling or Hard Modeling, drawing such diagrams prior to embarking on a study is frequently a useful activity to clarify one's thinking about a phenomenon.

Using PLS allows us to use a far more complex model—one with many LVs and many links. Frequently, when we are at the initial stages of our understanding, we do not have a crisp and elegant model. Instead, we may have a large and complex model for which we are not very sure which LVs are important and which are not. This is a circumstance for which PLS is ideally suited. Alternatively, some phenomena are inherently very complex and so we need complex models to understand them. Once again, PLS is ideal for this situation. Consequently, PLS has been used in the analysis of complex phenomena such as the impact of schools on learning, in a study in which 41 LVs were used (Noonan & Wold, 1985). When one cannot fully articulate the connections among the LVs, one can still use PLS in a manner somewhat analogous to stepwise multiple regression (Hui, 1982).

A model for our example is outlined in Figure 1A. In this figure, year-end reading level is shown to be affected directly by whole language instruction and pupil attitude. The use of whole language is influenced by teaching style. Pupil attitude is hypothesized to be affected by classroom environment, which is in turn influenced by school climate. Both teaching style and school climate are influenced by administrative structure.

Of course, other connections could be made between the latent variables if the investigator had a different model. Figure 1B shows another model based on the same variables. Reading level is hypothesized to be directly influenced by whole language instruction, teaching style, and pupil attitude. Additionally, it is hypothesized that teaching style is influenced by classroom environment, school climate, and administrative structure.

Step 3—Selecting Manifest Variables and Specifying the Outer Model

Once one has determined the LVs to be used in the model, one can turn to selecting the empirical variables for gathering the data. These variables, the ones used to collect data, are termed *manifest variables* (MVs). Notice that whereas LVs are conceptual entities, MVs are empirical entities (i.e., they are directly observable or measurable). For example, the diagnostic category, Attention-Deficit Disorder (ADD) is an LV, whereas a particular test or rating scale purported to measure ADD would be an MV. The specification of the MVs that are related to the LVs is termed the *outer model*.

In general, we would like to have three or more MVs per LV. All things being equal, the more MVs per LV, the more accurate our assessment of the LV. Because no MV is a perfect measure and all MVs measure more than one

FIGURE 1A MODEL I

FIGURE 1B MODEL II

FIGURE 1C MODEL III

FIGURE 1. Hypothetical outer models of latent variables.

thing, we tend to get a better estimate of the LV with multiple MVs. Through multiple measures, the common aspects of the MVs are accentuated and the noncommon aspects are minimized. The advantage of combining MVs is true not only for Soft Modeling and Hard Modeling, but also for any other research situation.

PLS offers more freedom than other modeling procedures in the number of MVs that can be used. Few limits are set by PLS on the number of MVs that may be used. One may even use more total MVs than participants, as long as the number of MVs associated with any LV is less than the number of subjects in the study. This freedom to use a large number of MVs is very useful when we have only a vague, or at least unclear, notion of which MVs are appropriate for the LVs.

Freedom to use many types of MVs is also present in PLS, unlike many hard modeling procedures (Bertholet, 1989). One may use dichotomous variables, such as gender, or any other variable based on the presence or absence of a characteristic (e.g., passing or failing a course). Unordered categorical MVs may also be used, such as types of learning difficulties or diagnostic categories. Ordinal variables—those in which participants are ranked on a particular characteristic—can also be used. Of course, interval and ratio level variables may also be used, such as scores on achievement or intelligence tests.

In the interest of brevity we will *not* specify all the MVs in our example. Instead, a subset of MVs for a single LV will be used to illustrate the point. When we consider the whole language instruction LV we may wish to select the following MVs: (a) a self-report measure of the teacher's belief about whole language and its components, (b) a self-report checklist of behaviors the teacher engages in when teaching reading, (c) an observer's checklist of reading instruction behavior, (d) an observer's holistic evaluation of the teacher's method based on interviews, and (e) students' descriptions of how they were taught to read. Thus, rather than saying one method is the royal road to describing whole language instruction and assuming that one measurement method is equivalent to the LV, we will use a composite based on five different measurements and perspectives. This composite will be our estimate of the whole language LV. Figure 2 represents the relation between the MVs and LV. If we completed the example, we would have similar diagrams for each LV.

Step 4—Gathering the Data

Although there are no specific requirements for gathering data for a study using PLS, Wold (1989) noted that PLS, like all methods, is subject to the GIGO Principle (Garbage In, Garbage Out). That is, the quality of any study rests on the quality of the information collected. As Baumrind (1983) and Martin (1982, 1987) have noted, many studies using Hard Modeling have failed to use high-quality data, probably because of the limited resources available. In the real world, with limited resources (e.g.,

time, money, and personnel), one is frequently forced to choose between gathering high-quality data (lengthy interviews, observation, complete tests) on a few participants or low-quality data on many participants (e.g., individual items or very short questionnaires). Unfortunately, many forms of Hard Modeling (e.g., LISREL) require large samples and realistically preclude the use of high-quality data. *Because PLS does not require large samples, it allows one to use high-quality data and thus allows the researcher to make the choice between quantity and quality.* It might be argued that the use of high-quality data is especially important in PLS, because it does not make assumptions about measurement error, as Hard Modeling does.

Step 5—Evaluation

Once we have gathered the data, we can evaluate how well our model matches the data. Soft Modeling, like Hard Modeling, requires a computer to calculate the information necessary for this step. Fortunately, there is an inexpensive and efficient computer program (Lohmoller, 1984) and an excellent and very readable manual for it (Falk & Miller, 1993). The output of the program provides the user with a value indicating the strength of each relation between LVs in the inner model, and between each MV and its corresponding LV in the outer model. As in Pearson correlations, these path coefficients can have values ranging from -1 to $+1$, with zero indicating no linear relation, -1 indicating a perfect negative relation, and $+1$ indicating a perfect positive relation. Thus, each line in Figure 1 would have a numerical value in this step, indicating the strength of the relation. The output also includes a value that can be used to evaluate the overall model.

Although various tests of significance may be used in evaluating PLS models (Lohmoller, 1989), it is frequently more useful to focus on how well the model predicts the outcome seen in the data (Falk & Miller, 1993). That is, it may be more useful to focus on the amount of variance explained rather than on statistical significance. When we focus on prediction, we are dealing with a continuum and not a dichotomy, as we do when we evaluate a model for statistical significance.

Frequently, and perhaps desirably, we may wish to select which of several competing models provides the best match to the observed data. Our goal should not be merely to see if *our* model matches the data, but to find the best, most plausible model for the phenomenon we are investigating. Unless we consider multiple models, we may test our favorite model and neglect a better one.

When selecting the best of the alternative models, we need not focus on the difference between models being statistically significant, we need only focus on selecting the one that leads to the best prediction. Similar evaluation strategies have been suggested for Hard Modeling (Tanaka, 1987).

In our example, we may find that Model II leads to a much better prediction of student learning than does

FIGURE 2. An example of a portion of the outer model.

Model I (see Figure 1). Consequently, we may wish to drop Model I from further consideration.

Although the overall model can be evaluated, it is often more useful to evaluate the components of the inner and outer models separately. In examining the outer model (the relations between the MVs and LVs), we focus on whether each MV belongs with the LV with which it was initially placed. When the MV does not relate highly to the model, we may find that it does not belong in the model at all, or we may find that it belongs with another LV. We may also find that a given LV may need to be divided into two separate ones. In our example, we may find that some of the manifest variables we thought measured the latent variable classroom environment (e.g., "children make fun of one another") is actually related to the latent variable of school environment.

When evaluating the inner model (the relations among the LVs), we are attempting to determine if the hypothesized links reflect a meaningful relation in the data. We also need to investigate whether a link exists among the LVs that we did not initially hypothesize. For example, we might find that classroom environment has a direct influence on reading level, rather than the indirect effect we originally hypothesized. We might also find that administrative structure influences whole language instruction as well as teaching style, while school climate affects teaching style and pupil's attitude.

Step 6—Revision

Based on the results from Step 4, we may wish to revise our model and reevaluate it. The revision may entail rearranging the relation between MVs and LVs and adding and/or dropping links between LVs. Once the revised model is evaluated, we may wish to further revise the model until we are satisfied that the best match between the data and model is obtained.

Of course in revising the model, we must *not* be guided solely by empirical results. We must consider the possibility and plausibility of the model. Even if it matches the data very well, a model will not be useful when it is impossible (e.g., when the model has a later event influence an earlier one, or when the model violates well-established principles). Again, we must be guided by both empirical findings and theory in our revisions and model construction.

Model III (Figure 1C) illustrates a revised model of our example based on the results of Step 5. Based on the results of the evaluation step, we now posit Model III, where whole language instruction, teaching style, classroom environment, and pupil's attitude all have a direct influence on reading level. Administrative structure influences whole language instruction and teaching style, and school climate affects teaching style and pupil's attitude.

At this point, we have a model of the phenomenon under study. The final model may or may not resemble any of the initial models. The cautious researcher may wish to replicate the study and evaluate with a PLS or with a harder model (e.g., LISREL). *At some point the implications of the model must be tested directly.*

We frequently develop models for policy decisions. Although models can suggest the existence of causal relations, they cannot confirm them (Baumrind, 1983). Models can help us formulate hypotheses and eliminate spurious relations, but they do not establish causality. They show only that connections are relevant. Ultimately, the only test that really matters is the evaluation of the policy decisions based on the model. This is true whether we are using PLS or any other modeling device. For example, in our model, we could find that administrative structure influences the teachers' use of whole language instruction and indirectly children's learning. We might then wish to include modification of administrative structure in our intervention and examine whether it improves the application of whole language.

EXTENSIONS OF PLS

We have just outlined the steps we might go through in conducting a study based Soft Modeling. This outline contains just the basic model and does not include any of its possible accessories. PLS models can contain types of elements that extend the basic model just examined. Perhaps the two most useful extensions for developmental psychologists and educators are hierarchical LVs and developmental functions. In hierarchical models, a hierarchical LV—an LV composed of other LVs—is used. For example, one study (Noonan, 1989) groups four LVs (teaching style, questioning, classroom management, and question type), each measured by several manifest variables, into a single hierarchical LV of active teaching. Hierarchical models are especially useful in large complex models, such as the evaluation of school systems (Noonan & Wold, 1983). In our example, we could have used a hierarchical LV—school—based on the LVs of classroom environment, school climate, and administrative structure.

If one wishes to conduct a development study, PLS can easily accommodate either a longitudinal or cross-sectional design. Falk and Miller (1991) outlined several different methods for examining developmental change with PLS. Researchers who are interested in conducting a developmental study using PLS may wish to consult the Falk and Miller article before designing their study. Returning to our example and model, we could use these methods if we wished to track children for a year or longer while they were exposed to whole language instruction.

COMPARISONS TO OTHER METHODS

Before ending our discussion of Soft Modeling and PLS, we will provide a brief overview of how PLS functions and how it differs from other procedures that may seem to be similar. Unlike the previous sections, some minimum familiarity with advanced statistics may be necessary to follow this section.

PLS is radically different from the more widely used Hard Modeling procedures based on Maximum Likelihood (ML) methods (e.g., EQS, LISREL, EZ-PATH). Although all employ MVs and LVs and specify the relations among the LVs, they do this in very different ways. In this section, we will briefly touch upon the differences. More detailed descriptions may be found in Jöreskog and Wold (1982) and Fornell and Bookstein (1982). In examining the differences between Soft Modeling and Hard Modeling, we are not trying to establish that one method is better than another. They should be seen as complementary (Wold, 1985).

In PLS, the estimates for each LV are solved one at a time, hence the name *partial* in partial least squares. A score is first calculated for each LV, with the constraint of unit variances, using principle component analysis. Next, an iterative procedure is used to estimate all the parameters using ordinary least squares, with the criteria of minimizing the residual on all variables, especially the MV. The weights given to the MVs in each LV are a function of their relation to the other LVs that are connected to the LV containing these MVs, in a manner similar to canonical correlations. This iterative process continues until stable estimates are established. Thus, PLS is part of the family of component analyses and ordinary least square methods.

In contrast, Hard Modeling procedures (see Moore, this issue) tend to be based on the maximum likelihood (ML) procedure and factor analysis. Unlike ordinary least squares estimates, ML makes many assumptions about the nature of the data. Consequently, ordinary least squares can be applied to a wider range of situations with a much smaller sample. Proponents of ML may claim that their method is not affected by violation of assumptions. Although this may be true for some assumptions in isolation, it is not true of all assumptions. We do not know what happens when multiple assumptions are violated, but we do know that the assumptions are likely to be violated in the real world. At times, ordinary least squares will provide a meaningful answer to problems when ML cannot (Fornell & Bookstein, 1982).

PLS also differs from ML by constructing the model in parts rather than simultaneously. Partial construction has the advantage that smaller sample sizes and more variables may be used. Calculations are much more rapid, leading to a much easier process of model evaluation and revision.

The emphasis in PLS is on prediction, whereas the emphasis in ML is on parameter estimation for the popu-

lation. Consequently, PLS uses statistics that are directly interpretable in terms of the reduction in errors of prediction based on the use of the model (e.g., the Stone-Geisser test of predictive relevance). This approach is most useful when we are interested in models that lead to better predictions than we currently have and less interested in whether they are "true" for some larger population. Outside of some pure experimental systems, we cannot have both strong prediction and strong parameter estimation (Wold, 1982), and we must choose which one we want and which one is more appropriate for our situation.

Hard Modeling is concerned with describing the invariant mechanisms that cause the observable data. Although most proponents of Hard Modeling do not claim that correlations can be used to prove causation (see Moore, this issue), they do use correlation-based methods to evaluate causal claims and models. Very strong assumptions need to be made in order for this goal to be reached. Often, we cannot make such assumptions and we must either ignore the consequences of violating the assumptions or adopt another method of modeling. Causal consistent statements—identification of invariant structural parameters—can be made only in a crisp, closed system with numerous theoretical assumptions. Perhaps the most telling assumption of Hard Modeling is the constraint of the closed system, in which all relevant variables are included. When a relevant variable is excluded, a specification error results and we may draw very faulty conclusions. Yet, in the real world we are unlikely to know all the relevant variables and parameters. Even if we know all the parameters in a complex open system, in time the system may change, new variables may enter the system, and old ones may leave the system. Such is the nature of an open system.

A disadvantage of PLS comes when one has a precise estimate of population parameters and a very explicit model to test. In such circumstances, ML procedures are superior. Wold (1985) and others have recommended that PLS be used as a preliminary stage for Hard Modeling.

The most important advantages of PLS over ML procedures are that (a) PLS does not require interval-scale measurement, (b) it is not sensitive to violations of multivariate normality, (c) it has no assumptions about independence of observations, (d) it is less hampered by collinearity among manifest variables than LISREL, and (e) it may be used with small sample sizes and even with more manifest variables than participants.

EDUCATIONAL APPLICATIONS

As noted in the *International Encyclopedia of Education* (Noonan & Wold, 1985), PLS is quite useful in a situation where there is a massive amount of data and poorly articulated theory. This is clearly the state of education. Although PLS is not widely known in the educational community of

North America, PLS has been used widely both in Europe and in such diverse areas as market research and chemistry in North America. Applications relevant to special education and education include (a) family-child interactions (Cowan, Cowan, Heming, & Miller, 1991; Engfer, 1988; Meyer, 1988); (b) school evaluations (Noonan & Wold, 1983); (c) the relations among motivation, cognition, and metacognition in school children (Schneider, Borkowski, Kurtz, & Kerwin, 1985); (d) the development of verbal ability (Broberg, Hwang, Lamb, & Bookstein, 1990); (e) school achievement (Keeves, 1986; Schneider & Bos, 1985); (f) learning difficulties (Ketterlinus et al., 1989); (g) behavior problems (Miller, Cowan, Cowan, Hetherington, & Clingempeel, 1993); (h) academic achievement of minority students (Hui, 1982); and (i) delinquency (Scheungrab, 1990).

THE FUTURE

Science, especially applied science, has discovered what we all knew—the world is a very complex place and our knowledge is very imprecise. In many situations, we may be incapable of ever having the precision and crispness necessary to apply existing methods of Hard Modeling, because of their stringent assumptions. This discovery has led to the development of new methods for dealing with uncertainty and vagueness. One of the new methods tailored to this situation is PLS. Future development may include the integration of PLS with other new methods, such as Fuzzy Logic (Azorin-Poch, 1989). Perhaps the future of educational research is not in a hard statistical model, nor in pure qualitative research, but in the world of Soft and Fuzzy methods. ■

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