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Research article

# Relationship between nitrogen and soil properties: using multiple linear regressions and structural equation modeling

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## Abstract
The aim of this work is; Firstable, to obtain an expression using multiple linear regressions to evaluate relationships between nitrogen and soil properties (organic matter OM, C to N ratio, clay, pH). Secondly, we perform a path analysis using structural equations modeling, in order to investigate simultaneously the interactions between the different components of the soil properties and their relationships with nitrogen. Using 2 groups of soils from Tunisia (Luvisols and Cambisols), we carried out multiple linear regressions integrating different soil physical and chemical properties and we searched those regressions with nitrogen. Results show that Luvisols and Cambisols presented different relationships among their properties. Thus, we searched equations for both groups of soils; (1) Luvisols: N=0.047 + 0.032OM + 0.001Clay +ε, and (2) Cambisols: N=0.007 + 0.021OM + 0.005Clay +ε. Using AMOS, the structural equations modeling allows, to test in a simultaneous analysis the entire system of variables, in order to determine the extent to which it is consistent with the data.

***Keywords:*** Nitrogen, soil properties, multiple linear regressions, structural equations modeling, Tunisia.


## 1. Introduction
Though "azote", the French name for nitrogen given by Lavoisier, means "lifeless" and inert, this element is a major constituent of living organisms which catalyze key steps in biogeochemical cycling (Pansu et al., 1997).

Nitrogen was predicted by different biochemical properties (Trasar-Cepeda et al., 1998), However, biochemical properties are also closely related to physical and especially chemical soil properties because of the dynamic and interactive nature of soil process (Schoenholtz et al., 2000).

MLR constitutes an accurate tool to evaluate soil quality, since it generates a minimum data set of indicators (Doran and Parkin 1996). MLR have been successfully used by different authors to evaluate soil quality, being used in natural forest soils balanced with the overall environment (Trasar-Cepeda et al. 1998) or in agriculture soils under different management (Lentzsh et al., 2005). The objective of the present work is: firstly, to establish a model using MLR based on different soil physical and chemical properties, in different zones from Tunisia, so that we can searched equations ($N = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon$ Where, N: the dependent variable and $X_1, X_2 .... X_n$: independent variables as well as the soil physical and chemical properties ) for both groups of soil. Then, all the variables would be included simultaneously into single model in order to test the interactions between the independents variables as well as their contributions on the dependent variable (N).

02 Thus, the objective of the present study was to develop statistical procedure to predict N from readily available soil properties for soils of the semi-arid and arid regions of the Mediterranean basin, using data available at the Tunisia scale.

## 2. Material and methods

### 2.1. Data Collection

Tunisia is situated northern Africa between the latitudes 32° and 38° north and between the longitudes 7° and 12° east. It is located at the junction of the western and oriental Mediterranean and covering a surface of 164000km$^2$. In spite of this small surface, nor the climate neither the vegetation are uniform. In fact, the geographical position and the general orientation of the main relieves are influenced at the North by the Mediterranean Sea and at the South by the Sahara. Concerning the Center, it is under the conjugated effect of these two elements. Even the dominance of calcareous rocks**,** geology consists of large range of type of rocks

We used a data base, of 218 elements; we study soil samples of 0-15 cm, depths two or three pits per plot. Samples were analyzed for texture (hydrometer method), pH (using pH meter), total nitrogen (khjeldal method), and organic matter (with carmograph).

The relationship between nitrogen and other soil parameters were investigated utilizing data from Tunisia. The database was constructed from soil profile information for soils pits surveyed by Tunisian research groups and the IRD (ex-ORSTOM) project, the Ministry of Agriculture of Tunisia (Direction de Sols) and Tunisian thesis reports. The data contained information for OM, pH, Clay and C/N.

### 2.2. Data Analysis

Descriptive statistics and multiple linear regression analyses were performed with SPSS. Multiple linear regression (MLR) analyses were carried out on all the data and according to soil groups.

**Table 1** Descriptive statistics for all the data

| | N | Min. | Max. | Mean | CV (%) * | SD* |
|---|---|---|---|---|---|---|
| Clay | 218 | 1 | 62.41 | 23.68 | 54.79 | 12.98 |
| Fine Silt | 218 | 0 | 44.68 | 19.12 | 56.99 | 10,89 |
| Coarse Silt | 218 | 3 | 58.6 | 14.69 | 59.51 | 8.74 |
| Fine Sand | 218 | 1.24 | 46 | 22.83 | 41.04 | 9.37 |
| Coarse Sand | 218 | 1.49 | 43 | 19.28 | 55.70 | 10.74 |
| pH | 218 | 5.6 | 8 | 6.97 | 11.37 | 0.79 |
| OC | 218 | 0.6 | 7.92 | 3.15 | 56.64 | 1.79 |
| OM | 218 | 0.9 | 13.72 | 5.49 | 55.47 | 3.04 |
| Nitrogen | 218 | 0.05 | 1 | 0.25 | 51.42 | 0.13 |
| C/N | 218 | 4.58 | 22.3 | 12.86 | 34.89 | 4.49 |

* CV = Coefficient of variation ; * SD = Standard deviation

The mean N value was 0.25 varying between 0.05 and 1 and had a CV of 51.42% (Table 1). All chemical properties, except pH and C/N measurements, had a coefficient of variation (CV) > 41%.

The procedure used was a stepwise linear regression, which allowed independent variable to be individually added or deleted from the model at each step of the regression. A MLR method was used because it is a practical tool that furnishes direct quantitative results, and also because the data set was not adapted to spatial analysis such as geostatitics due to lacking or imprecise geographic coordinates.

In the linear regressions, only parameters with statistical significance at the 0.01 significance level were considered for computing predictive equations and reporting results. Standard error of the prediction (SEP) and percentage of variance explained, through R$^2$ values, were used as means to evaluate the reliability of the models.

**Table 2** Summary of the linear regressions predicting Nitrogen

| | Model 1 : Cambisols | | | Model 2 : Luvisols | | |
|---|---|---|---|---|---|---|
| | β | t-value | Sig.t | β | t-value | Sig.t |
| Clay | 0.005 | 7.890 | 0.000 | 0.001 | 2.131 | 0.035 |
| OM | 0.021 | 11.76 | 0.000 | 0.032 | 25.79 | 0.000 |
| Const. | 0.007 | | | 0.047 | | |
| R | 0.957 | | | 0.941 | | |
| R $^2$ | 0.916 | | | 0.886 | | |
| Ad.R $^2$ | 0.915 | | | 0.884 | | |
| SE | 0.047 | | | 0.058 | | |
| F test | 525.780 | | | 450.278 | | |
| Sig. | 0.000 | | | 0.000 | | |

As can be seen in the case of all the MLR regression analyses, the Clay and OM measures are statistically significant in estimating the Nitrogen (P<0.00). The multiple R coefficient indicates that the correlation between soil properties and nitrogen is moderate (the two multiple R >0.94). According to R square statistic, 91.6% of the total variance for the estimation of nitrogen is explained by the first model. Similarly 88.6% of the total variance is explained by the second regression model, which estimates the nitrogen in the Cambisols and the nitrogen in the Luvisols respectively.

The models were also checked to see if they were prone to any multicollinearity effect. The variance inflation factor (VIF) values obtained were all close to one and thus, there was no evidence of multicollinearity (Hair et al. 1998). In terms of the relative importance of the estimation of a dependent variable, it can argued that the organic matter makes the largest contribution across the two models (the β coefficients hold the largest values). An examination of t-values also reveals an identical descending order of the factors that contribute to the estimation of nitrogen in both of soils (Bring, 1994).

The positive sign of the beta coefficients and t-values pertaining to these variables indicates that there is a positive relationship between nitrogen and the tow element of soil properties (OM and Clay). The selected equations for Luvisols and Cambisols; (i) Luvisols: N= 0.047 + 0.032 OM + 0.001Clay + ε, and (ii) Cambisols: N= 0.007 + 0.021 OM + 0.005 Clay + ε.

The plot of the predicted data against the observed shows that there is a good agreement of estimation (Fig.1 and Fig.2).

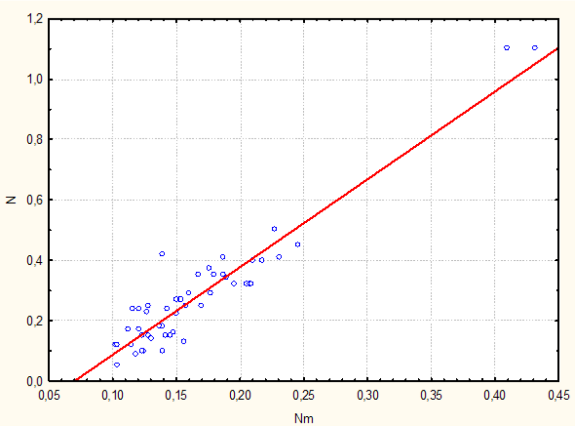


**Fig. 1** Luvisols

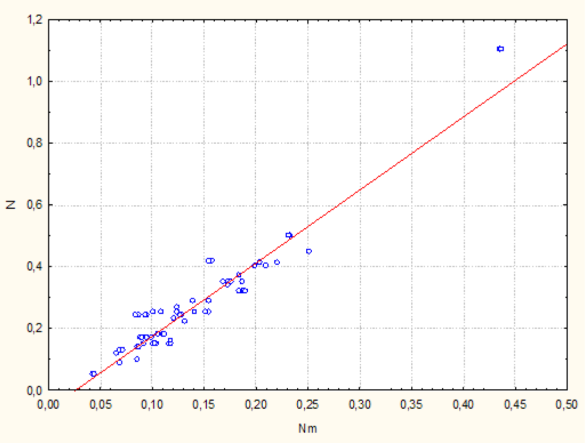


**Fig. 2** Cambisols

Where;
N: the measured nitrogen
Nm: the nitrogen calculated with the model.

The second step of our study consist to include simultaneously all the variables in a conceptual model in order to test the potential interactions between them. The structural equation modelling was used to achieve our aims.

### *2.3. Structural Equation Modeling (SEM)*

Structural equation modeling (SEM) is a statistical methodology that takes a confirmatory approach to the analysis of a structural theory bearing on some phenomenon. Typically, this theory represents "causal" processes that generate observations on multiple variables (Bentler, 1988). The structural equation modeling conveys that the causal processes under study are represented by a series of structural equations. And that these relations can be modeled. The model can then be tested statistically in a simultaneous analysis of the entire system of variables to determine to witch it is consistent with the data.

Several aspects of SEM set it apart from the older generation of multivariate procedure (Fornell, 1982). First, as noted earlier, it takes a confirmatory, rather than an explanatory, approach to the data analysis (although aspects of the latter can be addressed). Furthermore, by demanding that the pattern of intervariable relations be specified a priori, SEM lends itself well to the analysis of data for inferential purpose. By contrast, most other multivariate procedures are essentially descriptive by nature, so that hypothesis testing is difficult, if not impossible. Second, although traditional multivariate procedures are incapable of either assessing of correcting for measurement error, SEM provides explicit estimates of these error variance parameters (Byrne, 2001).

### *2.4. Modeling the Relationships between the different variables*

We developed a generalized conceptual model illustrated in Fig. 3 this model hypothesizes the potential interactions between the independents variables (OM, pH, clay, C/N) and their contributions on the dependent variable (N). The input variables were chosen because they are known to influence N (OM and soil texture) or because they are easily obtained (pH).

Net accumulation of nitrogen in soil is constrained by the amount of organic matter and it is minimum C to N ratio (Shiper et al., 2004, Daniel et al., 2007), it appears when the nitrogen accumulates the C to N ratio decline (Sparling and Shipper 2002). Sarrah et al., (2006) found that changes in soil pH significantly affect N and C to N ratio, soil ph often hypothesize to be a major factor regulating organic matter (Sarrah et al., 2006, Paul et Clark 1989). And Danniel et al., (2007) found significant correlation between clay and nitrogen, clay and organic matter, clay and pH. C to N ratio for two Mediterranean soils (Fersiallitic and Brown) were different, this is probably due to the clay soils (Pansu et al., 1997). In the MOMOS model C to N ratio evolution varied with the organic matter compartments.

Fig. 3 depicts the causal relationship among exogenous and endogenous variables. An exogenous variable whose causes lie outside the model. In these cause clay is the only exogenous variable in the structural model. In contrast to exogenous variables, the postulated causes of endogenous variables are included in the model. In the current model organic matter, C to N ratio, pH, and N are all endogenous variables.

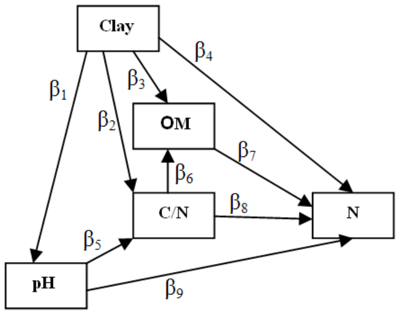


**Fig. 3** A conceptual model of factors influencing nitrogen

## 3. Results and discussion

All factor loadings that were tested had t-values greater than 1.96 all of the path coefficients were significant. The goodness of fit indices for the structural model that are shown in table 3 indicated the model has a good fit of the data.

**Table 3** Fit indices for the structural model

| GFI | AGFI | NFI | RFI | IFI |
|---|---|---|---|---|
| 0.99 | 0.98 | 0.99 | 0.99 | 1.00 |
| TLI | CFI | RMR | PGFI | RMSEA |
| 1.00 | 1.00 | 0.036 | 0.067 | 0.00 |

The root mean square (RMR) residual represents the average value across all standardized residuals, and ranges from 0 to 1; in a well-fitting model this value will be small than 0.05 (Byrne, 2001). Turning to table 3, we see that the RMR value for our model is 0.036; we can conclude that the model fit the data well.

The adjusted goodness of fit index (AGFI) differs from the goodness of fit index (GFI) only in the fact that it adjusts for the number of degree of freedom in the specified model. They address the issue of parsimony by incorporating a penalty for the inclusion of additional parameters. The GFI and AGFI can be classified as absolute index of fit (Hu and Bentler 1995). Although both index range from 0 to 1, with values close to 1 being indicative of good fit, Joreskog and Sorbom (1993), theoretically it is impossible for them to be negative; Fan, Thompson and Wang (1999) further cautioned that GFI and AGFI values can be overly influenced by sample size. Based on GFI and AGFI values reported in table 3 (0.99 and 0.98 respectively), we can once again conclude that our model fits the sample data fairly well.

Parsimony goodness fit index (PGFI), was introduced by James et al., (1982) to address the issue of parsimony in SEM. The PGFI takes in to account the complexity (i.e., number of estimated parameters) of the hypothesized model in the assessment of overall model fit, as such, “to logically interdependent pieces of information” the goodness of the fit of the model (as measured by the GFI) and the parsimony of the model, are represented by a simple index (the PGFI), thereby providing a more realistic of evaluation of the model (Mulaik et al., 1989). Typically, parsimony based indexes have lower than the threshold level generally perceived as acceptable for other normed indices of fit. Thus our finding of a PGFI value of 0.067 would see to be consistent with our fit statistics.

Normed Fit Index (NFI) has been the practical criterion of choice, as evidenced in large part by the current classic of status of its original paper (Bentler, 1992). However, addressing evidence that the NFI has shown a tendency to under estimate fit in small samples, Bentler (1990) revised the NFI to take sample size into account and proposed the CFI (Comparative Fit Index). Values for both the NFI and CFI range from 0 to 1. Each provides a measure of complete covariation in the data, although a value > 0.90 was originally considered representative of a well fiting model. (Bentler, 1992), a revised cut off value close to 0.95 has recently been advised (Hu and Bentler 1999). As shown in table 3, both the NFI (0.99) and CFI (1.00) were consistent in suggesting that the model represented an adequate fit of the data.

The relative fit index (RFI) (Bollen, 1986) represents a derivative of the NFI and the CFI, the RFI coefficient values range from 0 to 1 with values close to 0.95 indicating superior fit (Hu and Bentler 1999). The incremental index of fit (IFI) was developed by Bollen (1989) to address the issue of parsimony and sample size which were known to be associated with the NFI. As such its computation is basically the same as the NFI, except that degree of freedom are taken into account. Thus, it is not surprising that our finding of IFI = 1.00 is consistent with that the CFI in reflecting a well fitting model. Finally the Tucker Lewis index (TLI), Tucker and Lewis, (1973), consistent with the other index noted here, yields values ranging from 0 to 1 (Hu and Bentler, 1999).

The root mean square error of approximation (RMSEA) is one of the most criteria in covariance structure modeling. It takes into account the error of approximation and asks the question “how well would the model, with unknown but optimally chosen parameter values, fit the covariance matrix if it were available?” (Browne and Cudeck, 1993), values less than 0.05 indicate good fit. Turning to table 3, we see that the RMSEA value for our model is 0.000; we can conclude that the model fits the data well.

The general purpose of this study was to investigate simultaneously the interactions between the different components of the soil properties. Consistent with previous findings (Körschens, 1980; Nichols, 1984; Van Veen et al., 1984; 1985; Körschens, 1998) the capacity of soils to protect organic matter against microbial decomposition and microbial biomass against cell death or predation seems to depend on the soil clay content. Soil clay content is used as an abiotic factor modifying microbial decomposition activity or defining the size of protected pools of organic matter in models of soil organic matter turnover (Hansen et al., 1990; Franko, 1996; Molina, 1996; Patron, 1996).

Corinna Mertz et al., (2005) suggest that C to N ratio differ between the clay sub-fractions, organic matter in the fine clay contains more nitrogen than organic matter in the coarse clay.

The present study suggests that clay correlated with soil pH. In fact, Sarrah et al., (2006) found that exchangeable aluminium showed clear trends with soil pH, that is presents with a significant amount in clay.

Based on data from Springob and Kirchmann, (2002), Gyldenkaerne et al., (2005), suggested that organic matter is related to the soil C to N ratio. Thus, the organic matter would decrease when soil C to N ratio increase.

The C to N ratio relates the soil N (Springob and Kirchmann, 2003) as well as soil pH has an effect on the C to N ratio (Schmidt, 1982).

### *3.1. Effects of Exogenous and Endogenous Variables*

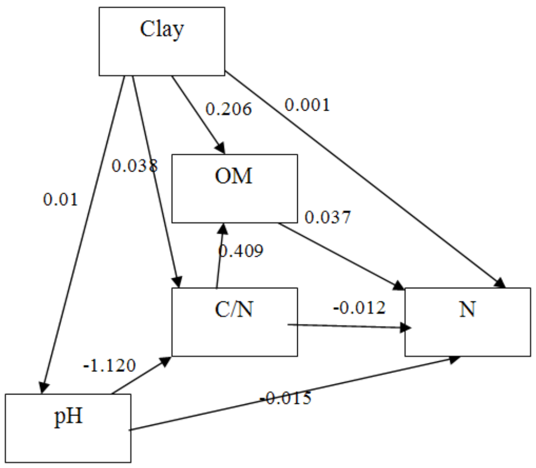


**Fig. 4** Effects of exogenous and endogenous variables

All parameter estimates in the model were significant at $\alpha$ = 0.05. The table 4 reports the coefficients for the paths in the model. They represented the strength of the direct effect of an exogenous variable on an endogenous variable, and that of one endogenous variable on another.

Bollen (1989) noted that the direct and indirect effects can help to answer important questions regarding the influence of one variable on another, but it is the total effect that is more relevent. He explained that the direct effect could be misleading when the indirect effect has an opposite sign, for in such cases the total effect may not be as strong as the direct effect shows.

The direct, indirect and total effects of all endogenous variables in the model are reported in table 4.

Direct effects, according to Bollen (1989) are the influence of on variable on another that are not mediated by any other variable. Indirect effects are ones that are mediated by at least one other variable, and the total effects are the sum of direct and indirect effects.

Indirect effects are calculated by multiplying all the path coefficients for each route of indirect influence.

If an independent variable has more than one route of indirect influence on a dependent variable, than the indirect effects for each route are summed to calculate the overall indirect effects of the independent variable on the dependent variable (Bollen, 1989).

The table 4 indicates that clay had a positive direct effect on nitrogen (0.001), organic matter (0.206), C/N (0.038) and pH (0.01), in addition clay also indirectly influenced N through organic matter, C/N, and pH.

Organic matter is directly and/or indirectly influenced by clay, C/N, and pH.

C/N had a stronger direct effect on organic matter (0.409), than did clay (0.206). In addition C/N also indirectly influenced nitrogen through organic matter as well as C/N is directly influenced negatively by pH and indirectly by clay through pH.

Clay not only directly contributed to nitrogen, But it also indirectly influenced nitrogen through 6 routes, the first route was through organic matter, the second was through C/N, the third was through ph, the forth was through C/N → organic matter → N
The fifth was through pH → C/N → organic matter N, while the last route was through pH → C/N → N.

Nitrogen was influenced positively by clay and organic matter and influenced negatively by C/N and ph. Organic matter had a stronger direct effect on nitrogen than did clay, C/N and pH.

While pH had the second strongest effect on nitrogen, its total effects was the highest in absolute value.

### *3.2. Validity Check*

In order to corroborate the validity of the model, we used a second database for verification. This database was made of 199 samples utilizing data from Tunisia.

**Tab. 4** Direct, indirect and total effects of exogenous and endogenous variables

| | pH | | | OM | | | C/N | | | N | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | D | I | T | D | I | T | D | I | T | D | I | T |
| **Clay** | .01 | - | .01 | .206 | .01 | .216 | .038 | -.011 | .026 | .001 | -.000185 | .0008 |
| **pH** | - | - | - | - | -.458 | -.458 | -1.120 | - | -1.12 | -.015 | -.0035 | -.018 |
| **C/N** | - | - | - | .409 | - | .409 | - | - | - | -.012 | .015 | .003 |
| **OM** | - | - | - | - | - | - | - | - | - | .037 | - | .037 |

The database was constructed from soil profile information for soils pits surveyed by Tunisian research groups and the IRD (ex-ORSTOM) project, the Ministry of Agriculture of Tunisia and Tunisian thesis reports.

**Table 5** Standard Regression Weighs and t-values

| Parameter | Sample 1 | | Sample 2 | |
|---|---|---|---|---|
| | Parameter value | t-value | Parameter value | t-value |
| $\beta_1$ | 0.01 | 2.521 | 0.012 | 2.759 |
| $\beta_2$ | 0.038 | 1.612 | 0.025 | 1.944 |
| $\beta_3$ | 0.206 | 12.043 | 0.195 | 10.852 |
| $\beta_4$ | 0.001 | 3.924 | 0.001 | 3.328 |
| $\beta_5$ | -1.120 | -2.936 | -1.315 | -3.349 |
| $\beta_6$ | 0.409 | 8.283 | 0.051 | 7.946 |
| $\beta_7$ | 0.037 | 54.446 | 0.037 | 52.004 |
| $\beta_8$ | 0.012 | -20.682 | -0.012 | -19.467 |
| $\beta_9$ | -0.015 | -5.087 | -0.015 | -4.977 |

**Table 6** Global Fit Indices

| Goodness of fit measure | Sample 1 | Sample 2 |
|---|---|---|
| Stand alone fit measure | | |
| $\chi^2$ | 0.690 | 0.542 |
| AGFI | 0.981 | 0.984 |
| GFI | 0.999 | 0.999 |
| RMR | 0.036 | 0.033 |
| RMSEA | 0.000 | 0.000 |
| Incremental Fit Measures | | |
| NFI | 0.999 | 0.999 |
| TLI | 1.00 | 1.00 |

Thus, although the $\chi^2$ static is significant for both samples ($p<0.01$) we conclude that the model has been validated successfully and can be seen as appropriate for the explanation and prediction of N.

## 4. Conclusion

The results indicated that MLR constitutes an accurate tool to evaluate relationships between nitrogen and soil properties. Soils with different characteristics, as Luvisols and Cambisols are, do not show the same relationships among their properties, mainly related to differences in soil organic matter content.

Moreover, it is worth noting that the SEM provides an adequate explanation of the simultaneously interactions between the variables included in the conceptual model. Whereas, as is the case with any research, the study presented exhibits the limitations that should be considered. First, we stress that this model is not designed to include all possible influences on nitrogen. We limit our consideration to the identified variables simply because the focus of the investigation is on the composite set links between clay, pH, organic matter, C/N and nitrogen. The obvious implication is the need for further consideration of similar composite models. Additional soil properties should also be included. For instance, potential measures can include the $CaCO_3$. Furthermore, the influence of bulk density, soil organic carbon and electrical conductivity (EC) might be a fruitful area of inquiry.

Although, structural equation modeling procedures deal with causal models, they do not establish causal relationships. Bollen (1989) asserts that "at best they show whether the causal assumptions embedded in a model much a sample of data". Thus, results of the study only verify that the proposed relationships among variables in the conceptual model were supported by the sample data collection for this study. An important next step is to fit the proposed model to other samples of data so that its validity can be examined. This limitation provides an opportunity for further research.

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