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Interrelations among Dimensions of Teaching Work: Potentialities of Structural Equation Modeling

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Abstract: *This article explores the application of Structural Equation Modeling (SEM) in the analysis of empirical education data, detailing its operationalization, result interpretation, and model quality assessment. SEM is a statistical technique that combines factor analysis and multiple regression, enabling the examination of dependency relationships between observed variables and latent constructs. The study uses data from the "Teaching Work in Basic Education in Brazil" research to analyze six constructs: preparation for career entry, activity control level, frequency of collaborative activities, classroom conditions, educational unit conditions, and professional satisfaction. The results show that preparation for career entry has the highest total effect on professional satisfaction, while the greatest direct effect is exerted by the activity control level construct. The article emphasizes the importance of theoretical support for defining items and associations in the model, as well as rigorous validation measures such as Cronbach's Alpha and fit indices (RMSEA, SRMR, CFI, TLI). The application to educational data demonstrates the potential of SEM to deepen the analysis of teaching work, highlighting its contributions to educational research and encouraging methodological advances and new research agendas in the field of Education.*

Keywords: *Structural Equation Modeling; Education; Quantitative Methodology.*

Introduction

The study of the relationships among factors that influence teaching work in basic education requires analytical approaches capable of capturing the complexity of these interactions. In recent years, the search for advanced quantitative methods has intensified, especially due to the need to understand how different dimensions—teacher training, working conditions, self-efficacy, professional satisfaction, among others—are articulated in teachers' daily lives. Despite this movement, there remains a theoretical and methodological gap in Brazilian educational literature concerning the application of Structural Equation Modeling (SEM), a technique widely established in the social sciences and psychology, but still underexplored in empirical research in Education. It is important to note, however, that teaching work represents only one of many possible applications of SEM in the educational field, as this approach is also useful for investigating issues such as school climate, learning processes, skill development, and public policy evaluation.

SEM, also known as covariance structure analysis or latent variable analysis, is a multivariate statistical technique that combines factor analysis and multiple regression. This approach allows researchers to simultaneously examine a set of dependency relationships between observed variables and latent constructs, as well as the associations among the constructs themselves (Hair *et al*., 2009). Due to its flexibility and robustness, SEM enables researchers to move beyond traditional analyses, integrating multiple factors into a single model and exploring both direct and indirect effects among variables. When analyzing the use of such models in the social sciences, Agresti and Finlay (2012, p. 595) summarized them as "versatile ways of conducting a wide variety of useful analyses in research."

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In the educational field, the potential of SEM lies in its ability to analyze constructs, which are concepts that cannot be directly observed and are measured through a set of items or variables (Neves, 2018). For this reason, theoretical support is essential to determine which items compose each construct under investigation. For instance, “preparation for career entry” is a concept that cannot be directly observed, but can be measured through indicators related to teachers’ perceptions of aspects such as content mastery, communication skills, and activity planning.

Among its possible applications, the technique stands out for its ability to estimate not only direct relationships among constructs, but also mediating and moderating effects, thereby providing an integrated view of educational phenomena. In international literature, studies have demonstrated associations between initial preparation and teacher self-efficacy (Darling-Hammond; Chung; Frelow, 2002), peer collaboration and professional development (Vescio; Ross; Adams, 2006), school environment conditions and job satisfaction (Skaalvik; Skaalvik, 2011; Vieira; Pereira Junior, 2020), and teacher autonomy and professional satisfaction (Pearson; Moomaw, 2005). However, it is worth noting that SEM enables the analysis of all these relationships within a single integrated and simultaneous model, enhancing the explanatory potential of analyses in the educational field.

This article aims to contribute to filling this gap by describing and discussing the application of SEM to observational microdata collected in a national survey on teaching work in Brazilian basic education. The text is organized into three sections, in addition to this introduction and the final considerations. The first section presents the methodological foundations and the criteria for model specification, interpretation, and evaluation. The second section details the empirical application in the educational field, covering the data source and the constructs analyzed. Finally, the third section presents the results and discusses the main contributions of the analysis.

Structural Equation Modeling

Structural Equation Modeling refers to a set of statistical techniques, among which factor analysis and regression analysis stand out. It offers the possibility to: estimate multiple and interrelated dependency relationships; represent concepts that are not directly observable; correct measurement error in the estimation process; and define a model to explain the entire set of relationships (Hair *et al*., 2009). It differs from other multivariate statistical techniques by considering not only the relationship of independent variables with the dependent variable, nor only the interdependence among explanatory variables. In the multiple associations allowed, a measure may be dependent at time (i) and independent at time (i + 1). Additionally, the graphical interface facilitates the understanding of the specified models.

As mentioned, SEM integrates the statistical techniques of factor analysis and linear regression. Factor analysis primarily aims to describe the original variability of a random vector in terms of a smaller number of random variables related to the original vector (Mingoti, 2005). The method used is Confirmatory Factor Analysis (CFA), whose confirmatory nature refers to the fact that the number of factors composing the model is defined *a priori*. This differs from Exploratory Factor Analysis (EFA), which does not require a prior definition of the number of constructs generated or the variables associated with them. Multiple regression, in turn, is a statistical method used to analyze the relationship between a single dependent variable and two or more independent variables. The purpose of regression is to predict changes in the dependent variable in response to variations in the independent variables (Neves, 2018).

Brief history

Regarding the origins of SEM, Pilati and Laros (2007, p. 206) state that it is "a data analysis technique with a hybrid origin, in at least three different sciences." According to the authors, the first and most well-known is psychometrics, developed in the early 20th century, especially in the seminal works of psychometricians such as Pearson, Spearman, and Thurstone. The second comes from studies, conducted around the same period, aimed at understanding aspects of animal morphology through path analysis. The last traces back to econometrics, developed in the mid-20th century, in which economists were interested in understanding macroeconomic phenomena by employing multiple regression equations. Over time, researchers improved and combined data analysis techniques from different fields of application until more robust procedures were established, as is the case with Structural Equation Modeling (Pilati; Laros, 2007).

The use of SEM became more frequent mainly due to "the increasing processing capacity of computers and more powerful and user-friendly statistical software" (Pilati; Laros, 2007, p. 205). This culminated in the launch of the journal *Structural Equation Modeling: A Multidisciplinary Journal* in 1994, dedicated to publishing empirical and theoretical articles from different fields of knowledge that employ this technique. In the Brazilian context, Pilati and Laros (2007, p. 206), working in the field of Psychology, observed that "since the mid-1990s, an increase in interest in the use of SEM as a data analysis strategy and theoretical model testing has been noticed."

Model assumptions

Regarding the statistical assumptions of this type of modeling, Kline (2012) specified that: 1) observations must be independent and the variables must be non-standardized; 2) there should be no missing data; 3) the joint distribution of the endogenous variables must be multivariate normal, which implies that endogenous variables should be continuous; and 4) exogenous variables need to be measured without error. It is worth noting that the requirement of multivariate normality is directly associated with the adoption of the Maximum Likelihood estimator, which is used to estimate model parameters and calculate the main fit indices.

However, Hair *et al.* (2009) adopt a more parsimonious approach by emphasizing the centrality of sample size, highlighting that as data deviate from the assumption of multivariate normality, the ratio between the number of respondents and the number of model parameters must be increased, recommending 15 respondents per estimated parameter.

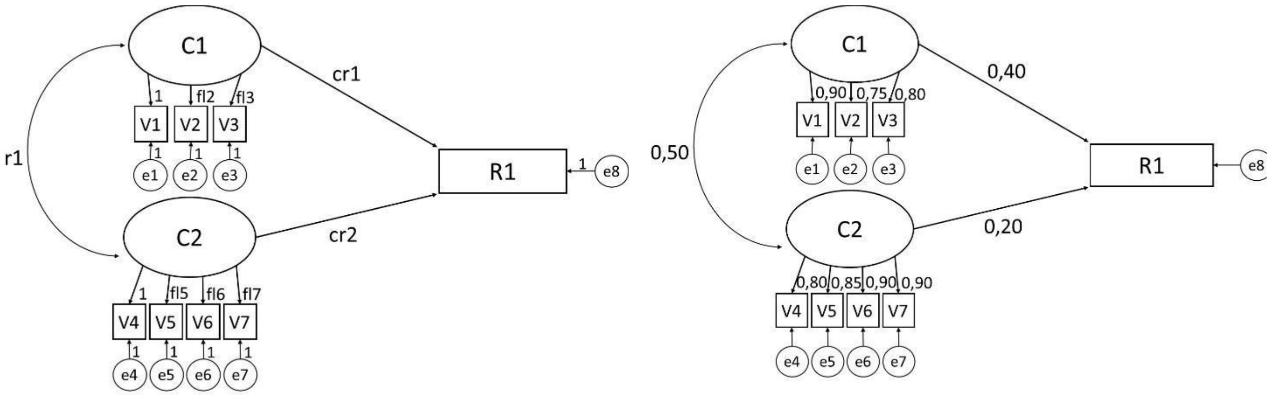
Currently, several software programs implement Structural Equation Modeling, such as the R software, which includes the Lavaan package for this purpose. Hox (1995) compared the results of this technique using AMOS, EQS, and LISREL software, finding that the three programs produced parameter estimates and standard errors that were very similar, but showed discrepancies in the model fit indices. Similarly, El-Shiekh, Abonazel, and Gamil (2017) demonstrated that AMOS, LISREL, and Lavaan (R) produced nearly identical parameter estimates, though with small differences in fit indices.

Model specification and interpretation

In this study, hypothetical models were used to simulate the application of SEM, providing information on how to specify and interpret the results. This strategy makes it possible to present the statistical principles involved and describe the procedures adopted. Supplying the knowledge necessary for the correct interpretation of results can help avoid reaching false conclusions. Such an explanation addresses the gap identified by Silva (2006, p. 15), who, in developing a study on SEM, noted that there is “little literature on how to conduct the modeling process; published articles usually only present the application, but few authors explain how results are obtained.”

It is assumed, then, an analytical model composed of two latent constructs (C1 and C2), seven observed variables (V1 to V7), eight error terms (E1 to E8), and one observed variable (R1). The graphical representation of the model is shown in Figure 1, displaying both the specification of the model and the results generated by the statistical software.

Figure 1: Specification and hypothetical results of the path diagram involving constructs C1 and C2 and the response variable R1.



Source: from the author (2025).

The specification of Structural Equation Modeling involves some parameters. In the graphical representation, the path diagram must be established by the researcher based on the following symbology: a) ellipses or circles represent latent variables and errors; b) rectangles or squares represent observed variables; c) single straight arrows indicate a dependency relationship between measures, starting from the independent variable and ending at the dependent variable; and d) double-headed curved arrows indicate an association—covariance or correlation—between variables.

Regarding terminology, SEM designates independent variables as exogenous variables and dependent variables as endogenous variables. In other words, endogenous variables are those that, at some point, depend on other variables, while exogenous variables never depend on others (Neves, 2018). This also applies to constructs: exogenous and endogenous constructs. In model specification, each endogenous construct must be associated with its respective error term. Measurement error exists because we cannot perfectly measure variables, particularly when analyzing more abstract or theoretical concepts and when respondents may feel uncertain about how to answer them (Hair *et al*., 2009).

Constructs C1 and C2 (Figure 1) refer to concepts that cannot be directly observed and are measured through a set of items. The graphical representation of the construct requires specifying the direction of the arrow between the construct and the measured items. An arrow going from the latent construct toward the measured variables indicates that the model is reflective. The reflective measurement theory assumes the “idea that latent constructs are the cause of the measured variables and that error results from the inability to fully explain these measures” (Hair *et al*., 2009, p. 598). Another variation is the formative model, in which arrows go from the measured variables to the latent construct. This perspective assumes the opposite, i.e., the measured variables constitute the cause of the construct, and error refers to the inability to fully explain the construct (Hoyle, 2012).

For each construct, the standardized coefficients estimated in the association with measured variables are referred to as factor loadings, which is the term used for the correlation between original variables and the unique factor (construct). The squared factor loading represents the percentage of variance in the original variable explained by the factor or construct. Thus, the higher the factor loading, the more important the variable is for the construct. The evaluation of factor loadings is based on adequacy levels. Hair *et al.* (2009) specified that factor loadings from 0.30 to 0.40 meet the minimum level for interpretation of the factor structure; loadings above 0.50 are considered practically significant; and loadings above 0.70 indicate a well-defined structure.

Another measure evaluated alongside the constructs is the extracted variance, considered an indicator of convergence, whose result indicates the average percentage of variance extracted. That is, it refers to the arithmetic mean of the squared standardized factor loadings of the component items. Values above 0.50 suggest adequate convergence.

In the hypothetical case, construct C1 included three measured variables (V1, V2, and V3), requiring the presentation of their respective factor loadings (fl1, fl2, and fl3) (Figure 1). However, the specified model retained c2 and c3 and fixed c1 at a value of one. The alternative of fixing the factor loading of one item at "1" consists of assigning a scale to the construct, since it is not directly observable (Hair *et al.*, 2009). Thus, the latent variable takes on the same metric as the construct. The technique of fixing one of the factor loading estimates at one is automatically employed in AMOS software.

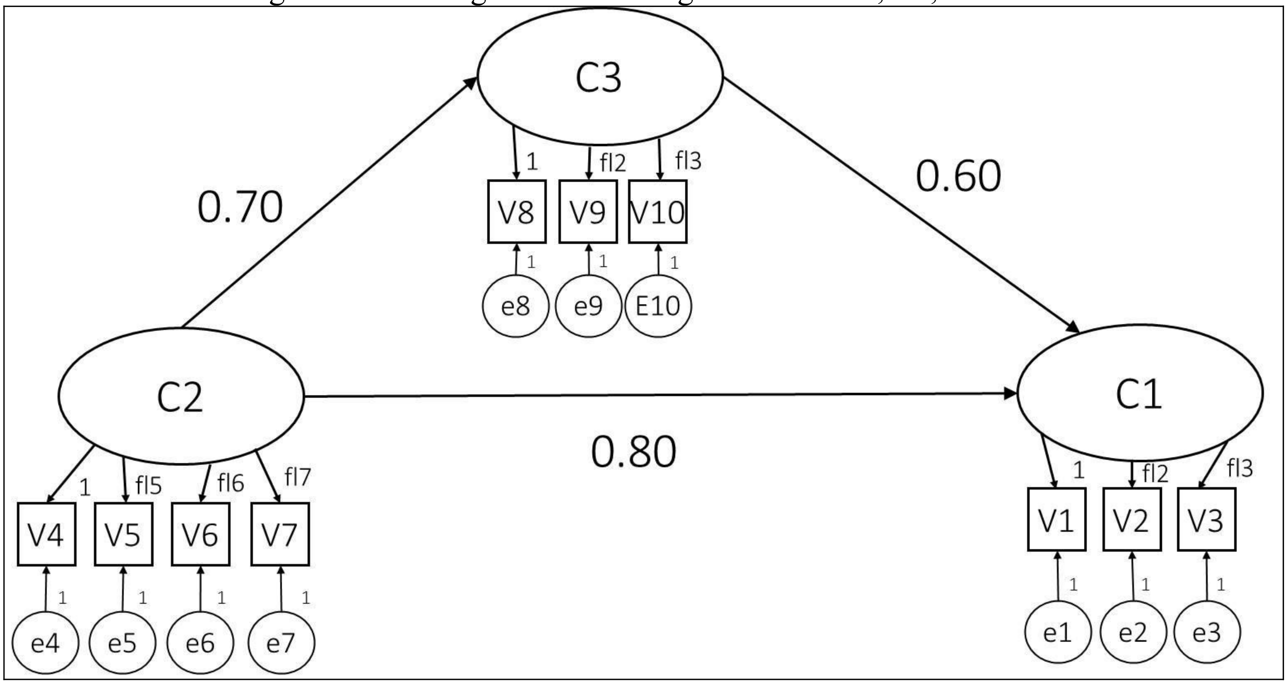
Figure 1 simulated SEM results, whose information is necessary for their interpretation. Starting with the latent variables, construct C1 was formed by items V1, V2, and V3, whose factor loadings were 0.90, 0.75, and 0.80, respectively. These loadings refer to the correlation between measured variables and the unique factor produced (construct). The results indicated statistical significance for all observed variables and presented a well-defined factor structure. It can also be stated that construct C1 explained 81% of the variance in V1, 56% of V2, and 65% of V3. These results were obtained by squaring the respective factor loading. The other construct (C2) was formed by observed variables V4, V5, V6, and V7, whose factor loadings were 0.80, 0.85, 0.90, and 0.90, respectively. The results were also statistically significant and presented a well-defined factor structure. The variance extracted by the construct corresponded to 64% for V4, 72% for V5, and 81% for V6 and V7.

Between constructs C1 and C2, a correlation (r1) was established, represented by a double-headed curved arrow. This numerical measure represents the strength of the relationship between two quantitative variables. The possible results range from -1 (perfect negative correlation) to 1 (perfect positive correlation), while values close to zero indicate no significant linear correlation between the two variables. In relation to the results, the two constructs presented a linear correlation coefficient of 0.50, meaning there was a positive association between C1 and C2 (Figure 1). In other words, as C1 increases, C2 is also expected to increase—and vice versa.

Another relationship established was the influence of construct C1 on the measured variable R1. This relationship (cr1) constitutes a linear regression, formed by the independent variable C1 and the dependent variable R1. Regression analysis aims to "estimate or predict the value of a variable based on fixed values of other variables" (Gujarati, 2000, p. 9). The result refers to the standardized regression coefficient, representing the expected variation in the dependent variable when the mean value of the independent variable changes. Standardization refers to the "procedure by which raw data are transformed into new variables, with mean 0 and variance 1" (Malhotra, 2001, p. 500). In relation to the results shown in Figure 1, the effect of construct C1 on R1 was twice the effect derived from construct C2.

Another potential of SEM is the possibility of considering not only the direct effect of a construct (or variable), but also the indirect effect. This occurs due to the multiple simultaneous associations permitted among variables. Consider a hypothetical situation consisting of three constructs (C1, C2, and C3) (Figure 2). In this model, direct relationships were established between C2 and C1 and between C3 and C1, as well as an indirect relationship between C2 and C1, mediated by C3. In this case, C3 plays a mediating role between the other constructs.

Figure 2: Path diagram considering constructs C1, C2, and C3.



Source: from the author (2025).

Taking into account the hypothetical results of the associations among constructs, the regression coefficient between C2 and C1 is 0.80, between C3 and C1 is 0.60, and between C2 and C3 is 0.70 (Figure 2). The results of direct, indirect, and total effects are shown in Table 1. Construct C3 exerts a direct effect only on C1. On the other hand, C2 directly affects both C1 (0.80) and C3 (0.70), and also indirectly affects C1 through C3. The calculation of the indirect effect is obtained by multiplying the regression coefficients along the given path, i.e., the product of 0.70 and 0.60. To obtain the total effect, the two types of effects are summed.

Table 1: Direct, indirect, and total effects of constructs C2 and C3 on construct C1.

Construct	Direct Effect	Indirect Effect	Total Effect
C2	0,80	0,42	1,22
C3	0,60	-	0,60

Source: from the author (2025).

The results of the direct, indirect, and total effects presented in Table 1 consider only C2 and C3 in relation to construct C1. It should be emphasized that this is only an illustrative example, and in models with more constructs, the same procedure can be used to calculate direct, indirect, and total effects among any combinations of constructs, according to the specified model.

The description of aspects related to SEM specification sought to facilitate the operationalization and interpretation of results. After simulating hypothetical analytical models, the next section presents the set of procedures necessary to assess the quality of the developed modeling

Model fit assessment

As mentioned, constructs represent theoretical concepts measured through a set of items or variables. The quality of these constructs can be assessed based on compliance with a series of criteria. In discussing the construction of multiple-item scales, Hair *et al.* (2009) established four basic criteria to be verified: (1) conceptual definition; (2) dimensionality; (3) reliability; and (4) validity.

The conceptual definition is the starting point for developing a construct, as it specifies “the theoretical basis for the multiple-item scale by defining the concept to be represented in terms applicable to the research context” (Hair *et al*., 2009, p. 125). Constructs are inadequate when the concept is poorly represented, either because the existing theory does not allow proper specification of the items to be observed or because the data collection instrument is not the best option for measuring the concepts. This stage of research is important because “[a] multiple-item scale is only as good as the items used to represent the construct; even if it passes all empirical tests, it is useless without theoretical justification” (Hair *et al*., 2009, p. 127).

Dimensionality evaluates whether items are strongly associated with each other and represent a single concept (unidimensional). The dimensionality of a set of items is assessed using Exploratory Factor Analysis (EFA), which aims to describe the variability of a set of variables in terms of a reduced number of factors (Mingoti, 2005). In other words, it allows the analysis of interrelations among a large number of variables and explains them in terms of their common inherent dimensions (Hair *et al*., 2009). The analysis is exploratory because it does not stipulate, a priori, the number of factors to be formed. It verifies whether the component items of the construct can be represented by a single factor.

The adequacy of the factor analysis model can be assessed through two measures. The first, called KMO (Kaiser-Meyer-Olkin), provides the model’s fit coefficient to the data used. Malhotra (2008) argues that values between 0.50 and 1.00 indicate that factor analysis is appropriate. Values below 0.50 suggest that factor analysis may be inadequate, requiring corrective measures such as excluding variables. The second measure is Bartlett’s test of sphericity, which verifies whether the variables are correlated with each other. The hypothesis test examines whether the population correlation matrix is close to the identity matrix, which corroborates the model’s fit quality.

Reliability refers to the degree of consistency among multiple measures of a variable (Hair *et al.*, 2009). When dealing with constructs, items must be intercorrelated since they measure the same concept. The statistic used to check reliability is Cronbach’s alpha coefficient, which shows the extent to which the scale produces consistent results (Malhotra, 2001). This coefficient ranges between 0 and 1, and values below 0.60 generally indicate unsatisfactory internal consistency reliability.

Validity characterizes the degree to which a scale or set of measures accurately represents the concept of interest. Content validity, or face validity, evaluates the correspondence between the variables included in a multiple-item scale and the conceptual definition. According to Hair *et al*. (2009, p. 125), this type of validity "subjectively assesses the correspondence between individual items and the concept through expert evaluations, pretests with multiple subpopulations, or other means." Thus, the researcher's challenge begins with defining the theories and concepts to be investigated and extends to how items are properly expressed. Beyond translating the theoretical approach into practical terms, the items must also be correctly and similarly understood by respondents. Failures at this stage of representing concepts or theories may result in measurement errors, and even sophisticated statistical techniques cannot produce satisfactory adjustments in the presence of such flaws.

Another type of validity is nomological validity, which verifies whether the construct exhibits the relationships predicted by theory or prior research. This type of validity is assessed through analytical models in which constructs and measured variables are associated according to the theoretical knowledge produced on the subject.

Empirically, there are measures to attest to the validity of a Structural Equation Modeling application. These include absolute fit measures, which "provide the most basic assessment of how well a researcher's theory fits the sample data" (Hair *et al*., 2009, p. 568), and incremental fit measures, which "evaluate how well a specified model fits relative to an alternative baseline model" (Hair *et al*., 2009, p. 570).

For SEM absolute fit, two criteria are evaluated. The first is the Root Mean Square Error of Approximation (RMSEA), which measures how well a model fits a population rather than just the sample used for estimation (Hair *et al*., 2009). The second is the Standardized Root Mean Square Residual (SRMR), which assesses the precision of the model's covariance or variance estimates (Hair et al., 2009).

Incremental fit indices are also analyzed using two criteria. One is the Comparative Fit Index (CFI), which evaluates how well a specified model fits relative to an alternative baseline model (Hair *et al*., 2009). The other is the Tucker-Lewis Index (TLI), which provides a mathematical comparison between a theoretical measurement model and a null baseline model (Hair *et al*., 2009).

Chart 1 presents reference values for each of these quality criteria (absolute and incremental fit). While Hair *et al*. (2009) allow greater variation in acceptable values, Hu and Bentler (1999) and Marsh, Hau, and Wen (2004) adopt stricter cutoff values for characterizing model quality.

Chart 1: Reference values for verifying the adequacy of quality criteria in structural equation models.

Criteria	Reference Values
RMSEA	< 0.10 (HAIR *et al*., 2009) < 0.06 (HU; BENTLER, 1999; MARSH; HAU; WEN, 2004)
SRMR	Non-specific (HAIR *et al*., 2009) < 0.08 (HU; BENTLER, 1999; MARSH; HAU; WEN, 2004)
CFI	> 0.90[(1)] (HAIR *et al*., 2009) ≥ 0.95 (HU; BENTLER, 1999; MARSH; HAU; WEN, 2004)
TLI	> 0.90[(1)] (HAIR *et al*., 2009) ≥ 0.95 (HU; BENTLER, 1999; MARSH; HAU; WEN, 2004)

Source: from the author (2025).
Note: [(1)] This reference should only be used when the number of measured items exceeds 30 and the sample size is greater than 250.

In empirical studies, the criteria presented in this section should always be considered. If they are not met, corrective measures must be adopted.

Application in the educational field

This section presents the data source and the constructs used in the analytical model applied to education.

Data source

The study used microdata from the research Teaching Work in Basic Education in Brazil, conducted by the Research Group on Educational Policy and Teaching Work (Gestrado) at the Federal University of Minas Gerais, across seven Brazilian states between 2009 and 2010. The survey analyzed working conditions in basic education schools, forms of school organization and management, impacts on teachers' health, changes brought by new educational regulations, among other aspects experienced by these professionals in the educational context.

The probabilistic and representative sample of the universe consisted of 6,684 teachers, covering 421 public or publicly contracted educational units in 35 municipalities located in the states of Minas Gerais, Pará, Paraná, Goiás, Espírito Santo, Rio Grande do Norte, and Santa Catarina. The study was restricted to schools located in urban areas.

Constructs analyzed

Structural Equation Modeling was developed in this study based on six constructs. Below, each concept and its component items are described.

Preparation for career entry refers to teachers' level of readiness when they began their professional activities in education. The teaching profession requires specific skills for carrying out the teaching–learning process, linked to interactions with students, school management, colleagues, and families. This construct is composed of nine variables related to teachers' perceptions of their level of preparation at the start of their careers, measured on a four-point scale (1. Very well prepared; 2. Well prepared; 3. Reasonably prepared; 4. Unprepared). According to the questionnaire, the formulation was: "When you began your activities in education, how did you feel regarding…?" From this prompt, nine evaluative items were proposed: (1) subject-matter/methodological management (didactics); (2) assessment of student learning; (3) communication with students/children (inside or outside the classroom); (4) communication with parents; (5) teamwork/collaboration with colleagues; (6) knowledge of school administrative aspects; (7) planning of activities; (8) knowledge of how children/youth learn and develop; and (9) knowledge of health, care, and basic needs of children/youth.

Activity control level represents teachers' level of control over the set of activities—inside and outside the classroom—carried out in their daily work (Gestrado, 2015). In the classroom, this includes aspects such as content, methods, teaching approaches, and student assessment. Outside the classroom, it involves criteria such as organizing work time and selecting teaching materials. This construct used a four-point scale (1. High; 2. Moderate; 3. Low; 4. None) and included six variables. According to the questionnaire: "How much control do you think you have over": (1) selecting content covered in lesson plans; (2) teaching methods and approaches; (3) choice of teaching materials; (4) student assessment; (5) definition of activities; and (6) organization of work time.

Frequency of collaborative activities with colleagues represents how often teachers engage in meetings at schools with their peers to address teaching-related issues. These range from classroom situations to broader and more formal aspects (Gestrado, 2015). This construct used a four-point scale (1. Always; 2. Frequently; 3. Rarely; 4. Never) and included six variables. According to the questionnaire: "How often do you carry out the following activities with your colleagues": (1) advising and/or counseling; (2) discussing the school's pedagogical project; (3) exchanging experiences about teaching methods; (4) exchanging experiences about teaching content; (5) discussing students; and (6) jointly participating in professional training/continuing education activities.

Perception of classroom conditions expresses "the adequacy level of the classroom—the place where teachers usually spend most of their working time" (Gestrado, 2015, p. 131). Adequate environmental and structural conditions favor both teaching and student learning. This construct was measured using a four-point scale and included four variables. According to the questionnaire: "How do you assess aspects related to your classroom's working conditions?": (1) ventilation; (2) lighting; (3) wall conditions; and (4) noise inside the classroom.

Perception of school unit conditions refers to teachers' evaluation of school infrastructure (Gestrado, 2015). This construct assesses physical spaces and the materials and equipment used in student activities. Measured on a four-point scale (1. Excellent; 2. Good; 3. Fair; 4. Poor), it consists of four items. According to the questionnaire: "How do you assess aspects related to the working conditions of this school unit?": (1) a designated lounge/rest area for teachers; (2) staff restrooms; (3) equipment (TV, video, audio, etc.); and (4) teaching resources (blackboard, photocopies, textbooks, etc.).

Professional satisfaction represents the "level of fulfillment that basic education teachers feel when carrying out their teaching activities, as well as their expectations about their professional future" (Gestrado, 2015, p. 143). It relates to teachers' motivation and attitudes toward their work, as well as their propensity to leave the profession. This construct is measured on a four-point scale (1. Always; 2. Frequently; 3. Rarely; 4. Never) and is composed of four variables. According to the questionnaire: "How often do the following statements correspond to your professional experience?": (1) frustration with work; (2) thinking about leaving education; (3) working in education brings great satisfaction; and (4) would still choose education if they had to restart their professional life.

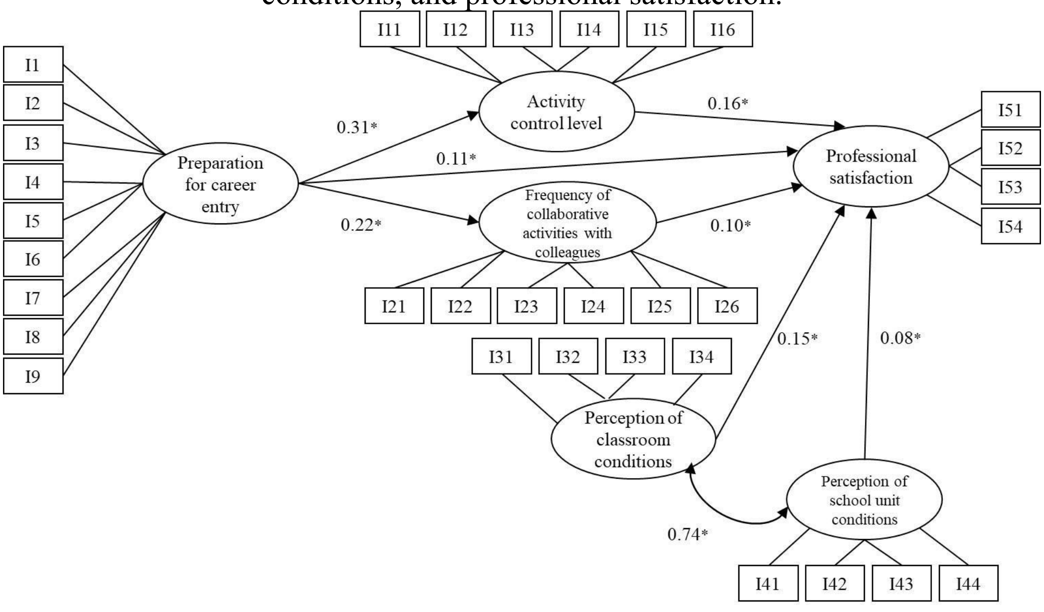
Based on the constructs presented, the following section introduces the research results. However, it is important to emphasize that the objective of this section is not to theoretically discuss teaching work in basic education. The focus of the article is on highlighting the potential applications of Structural Equation Modeling in this field, using empirical data as a methodological illustration.

Results

This section presents the application of Structural Equation Modeling to data on teaching work in basic education. In addition to showing results from an empirical study in the educational field, it aims to illustrate the analytical possibilities offered by SEM.

The analytical model established allows us to confirm the following direct associations: a) the influence of preparation for career entry on activity control level; b) the influence of preparation for career entry on the frequency of collaborative activities with colleagues; c) the dependence of professional satisfaction on activity control level; d) the dependence of professional satisfaction on the frequency of collaborative activities with colleagues; e) the dependence of professional satisfaction on the perception of classroom conditions; f) the dependence of professional satisfaction on the perception of school unit conditions; g) the correlation between the perception of classroom conditions and school unit conditions; and h) the dependence of professional satisfaction on preparation for career entry (Figure 3).

Figure 3: Path diagram involving constructs: preparation for career entry, activity control level, frequency of collaborative activities, perception of classroom conditions, perception of school unit conditions, and professional satisfaction.



Source: from the author (2025).
Notes: Standardized coefficients (*p<0.01).
Model fit statistics: RMSEA = 0.039; SRMR = 0.0576; CFI = 0.919; TLI = 0.914.

n = 6,684.
Legend: I1: Subject-matter/methodological management; I2: Assessment of student learning; I3: Communication with students; I4: Communication with parents; I5: Teamwork and/or collaboration with colleagues; I6: Knowledge of school administrative aspects; I7: Activity planning; I8: Knowledge of how children/youth learn and develop; I9: Knowledge of health, care, and basic needs of children/youth; I11: Selection of content in lesson plans; I12: Teaching methods and approaches; I13: Choice of teaching materials; I14: Student assessment; I15: Definition of activities; I16: Organization of work time; I21: Advising and/or counseling activities; I22: Discussion of the school's pedagogical project; I23: Exchange of experiences about teaching methods; I24: Exchange of experiences about teaching content; I25: Discussion about students; I26: Joint participation in training/professional development activities; I31: Ventilation; I32: Lighting; I33: Condition of walls; I34: Noise inside the classroom; I41: Teacher lounge/rest area; I42: Staff restrooms; I43: Equipment; I44: Teaching resources; I51: Frustration with work; I52: Thinking about leaving education; I53: Working in education provides great satisfaction; I54: Would choose to work in education if I had to restart my professional life.

The model specification was based on theoretical and empirical evidence from the educational literature, with each association among constructs supported by prior studies. This alignment situates the present study within national and international discussions on teaching work.

Specifically, the association between preparation for career entry and activity control level is supported by Darling-Hammond, Chung, and Frelow (2002), who demonstrated that teachers with stronger initial preparation tend to show greater self-efficacy and mastery of professional practices. The relationship between preparation for career entry and the development of collaborative activities with colleagues is supported by Vescio, Ross, and Adams (2006), who highlighted the importance of collective structures for teacher development. The influence of classroom and school conditions on professional satisfaction was identified by Vieira and Pereira Junior (2020), underscoring the relevance of the physical environment for teacher satisfaction. Collaborative work with colleagues showed a direct association with professional satisfaction in the study conducted by Skaalvik and Skaalvik (2011), which also used SEM as an analytical technique. Teacher autonomy, related to activity control, was found to have a positive impact on professional satisfaction, as demonstrated by Pearson and Moomaw (2005). The relationship between preparation for career entry and professional satisfaction was observed by Alves, Azevedo, and Gonçalves (2014), evidencing the importance of initial training for motivation and career persistence. Finally, the association between classroom and school unit conditions was noted by Servilha, Leão, and Hidaka (2010), who emphasized how school physical characteristics affect teachers' working conditions.

Returning to the analysis, Hair *et al*. (2009) point out that SEM assumes at least 15 respondents per parameter. The analytical model developed included 123 parameters to be estimated, which would require at least 1,845 respondents. This requirement was fully met, considering the sample of 6,884 basic education teachers.

Regarding the criteria for verifying model quality, the first was conceptual definition. In this respect, the data collection instrument was developed based on an extensive literature review and included contribairutions from researchers from various groups working on this subject. Beyond the content, the instrument's construction carefully considered both what should be asked and how questions should be phrased.

The verification of construct unidimensionality required the use of Exploratory Factor Analysis (EFA), with results presented in Table 2. The EFA results confirmed that all six constructs met this criterion, since the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy exceeded 0.50 in all cases, and Bartlett's test of sphericity was statistically significant ($p < 0.05$).

Construct reliability was assessed using Cronbach's alpha coefficient, which measures the internal consistency of multiple items for the same variable. The results for all six constructs were above 0.60, indicating satisfactory reliability (Table 2). The coefficients ranged from 0.670 (perception of classroom conditions) to 0.830 (preparation for career entry).

Table 2: Statistics for verifying unidimensionality and reliability criteria of constructs.

Construct	Number of Items	KMO	Bartlett's Test	Cronbach's Alpha
Preparation for career entry	9	0.873	0.000	0.830
Activity control level	6	0.716	0.000	0.731
Frequency of collaborative activities	6	0.828	0.000	0.815
Perception of classroom conditions	4	0.694	0.000	0.670
Perception of school unit conditions	4	0.719	0.000	0.733
Professional satisfaction	4	0.777	0.000	0.791

Source: from the author (2025).

The RMSEA and SRMR indices, related to the model's adequacy not only to the sample but to the population as a whole, and to the precision of estimates, respectively, met the strictest fit criteria. The RMSEA obtained was 0.039, which is within the 0.06 upper limit established by Hu and Bentler (1999) and Marsh, Hau, and Wen (2004). The SRMR was 0.0576, also below the maximum threshold (< 0.08).

The CFI and TLI statistics assess whether alternative models exist. Stricter acceptance criteria require values above 0.95 (Hu & Bentler, 1999; Marsh, Hau & Wen, 2004). The CFI obtained was 0.919 and the TLI 0.914, which, although below the strictest references, fall within the acceptable range indicated by Hair *et al*. (2009). Model respecification could involve adding new variables, excluding items, or modifying originally specified paths.

Constructs are composed of multiple items, and the intensity of each item is measured through factor loadings, which correspond to correlations with the construct's unique factor. Preparation for career entry had one item with a factor loading of 0.476, which meets the minimum threshold for interpretation (Table 3). Perception of classroom conditions had one item (0.293) below the minimum threshold. However, in both cases, the items were retained because theory identifies them as important for characterizing the constructs.

Another measure examined was extracted variance, operationalized through factor loadings. Constructs presented results below the desirable 50% threshold (Table 3). Although they did not achieve ideal levels of explained variance, they remain theoretically relevant for analyzing teachers' working conditions. This represents the first attempt at measuring these constructs; future research should improve their quality by modifying, adding, or removing items.

Table 3: Factor loadings and variance extracted for each construct's items. (Continue)

Items	Factor Loading	Variance Extracted
Preparation for career entry		34.1%
Subject-matter/methodological management	0.569	
Assessment of student learning	0.670	
Communication with students	0.556	
Communication with parents	0.538	
Teamwork/collaboration with colleagues	0.592	
Knowledge of school administrative aspects	0.570	
Activity planning	0.622	
Knowledge of how children/youth learn and develop	0.642	
Knowledge of health, care, and basic needs of children/youth	0.476	
Activity control level		33.1%
Selection of content in lesson plans	0.493	
Teaching methods and approaches	0.633	
Choice of teaching materials	0.653	
Student/child assessment	0.534	
Definition of activities	0.580	
Organization of work time	0.542	
Frequency of collaborative activities with colleagues		46.7%
Advising and/or counseling	0.594	
Discussion of the school's pedagogical project	0.661	
Exchange of experiences about teaching methods	0.791	
Exchange of experiences about teaching content	0.845	
Discussion about students/children	0.555	
Joint participation in training/professional development activities	0.607	

Table 3: Factor loadings and variance extracted for each construct's items. (Final)

Items	Factor Loading	Variance Extracted
Knowledge of health, care, and basic needs of children/youth	0.476	
Perception of classroom conditions		37.4%
Ventilation	0.655	
Lighting	0.699	
Condition of classroom walls	0.702	
Noise inside the classroom	0.293	
Perception of school unit conditions		39.6%
Teacher lounge/rest area	0.558	
Staff restrooms	0.645	
Equipment (TV, video, audio, etc.)	0.688	
Teaching resources (blackboard, photocopies, textbooks, etc.)	0.620	
Professional satisfaction		48.4%
Feeling frustrated with work	0.602	
Thinking about leaving education	0.728	
Working in education brings me great satisfaction	0.745	
Would still choose education if I had to restart my professional life	0.698	

Source: from the author (2025).

The regression coefficients among constructs were also analyzed, as shown in Figure 3 and Table 3. All five constructs had direct associations with professional satisfaction, with the strongest effects being activity control level (0.16) and perception of classroom conditions (0.15). However, preparation for career entry had the largest total effect on the final variable (Table 4), since it was the only construct exerting both direct and indirect effects on professional satisfaction.

Table 4: Direct, indirect, and total effects of constructs on professional satisfaction.

Construct	Direct Effect	Indirect Effect	Total Effect
Preparation for career entry	0.11	0.07	0.18
Activity control level	0.16	-	0.16
Frequency of collaborative activities with colleagues	0.10	-	0.10
Perception of classroom conditions	0.15	-	0.15
Perception of school unit conditions	0.08	-	0.08

Source: from the author (2025).

In summary, the results showed that all constructs were significantly associated with professional satisfaction, with particular emphasis on preparation for career entry, which had the largest total effect. These findings highlight the relevance of multiple dimensions of teachers' daily work and demonstrate the potential of Structural Equation Modeling for integrating diverse factors within a single analytical model.

Final considerations

Structural Equation Modeling is underutilized in Brazilian educational literature, especially in empirical investigations that aim to understand the complexity of relationships among different dimensions of teaching work. This study sought to partially address this gap by presenting, in a detailed and applied manner, the procedures for operationalizing, validating, and interpreting SEM results using an extensive and representative dataset of basic education teachers.

Among the main contributions, the study demonstrates that SEM enables, within a single analytical model, the simultaneous analysis of multiple constructs relevant to understanding school life—such as preparation for career entry, activity control level, frequency of collaborative activities, perception of classroom conditions, perception of school unit conditions, and professional satisfaction. The article shows how SEM allows not only the evaluation of direct effects but also the estimation of indirect and total effects, thereby expanding the explanatory power of analyses and providing an integrated view of the factors that affect teaching work. Furthermore, by aligning each modeled association with theoretical and empirical foundations from the literature, the study reinforces SEM's potential for advancing educational research with both statistical rigor and theoretical relevance.

The analysis carried out, for example, indicates that preparation for career entry exerted the greatest total effect on teachers' professional satisfaction, underscoring the importance of policies for initial and continuing teacher education. This finding reinforces the need for investments in evidence-based teacher training programs that integrate content, methodologies, and collaborative practices.

As next steps, future studies are encouraged to explore SEM applications across different levels and segments of basic education, expanding the variety of constructs and incorporating new dimensions, such as school climate, pedagogical management, curricular innovation, and educational inclusion. Longitudinal analyses are also recommended to assess causal relationships and construct development over time, as well as comparative investigations across different school systems and educational contexts. It is expected that this article will encourage other researchers to adopt SEM in their investigations, strengthening the methodological basis of the field and broadening the dialogue between theory, empirical evidence, and educational policy.

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Conflicts of interest and the use of artificial intelligence

The author declares that there are any conflicts of interest related to this article. The author also declares that artificial intelligence tools were used solely to assist in the translation of the manuscript into English and were not employed in any other stage of the scientific production.

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