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STRUCTURAL EQUATION MODELING IN THE EVALUATION OF SCHOOL FOOD SERVICE QUALITY: EVIDENCE FROM IFRO

MODELAGEM DE EQUAÇÕES ESTRUTURAIS NA AVALIAÇÃO DA QUALIDADE DOS SERVIÇOS DE ALIMENTAÇÃO ESCOLAR: EVIDÊNCIAS DO IFRO

MODELOS DE ECUACIONES ESTRUCTURALES PARA LA EVALUACIÓN DE LA CALIDAD DE LOS SERVICIOS DE ALIMENTACIÓN ESCOLAR: EVIDENCIA DE IFRO

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ABSTRACT

This paper presents a study on the application of Structural Equation Modeling (SEM) in evaluating the quality of services provided by a school restaurant at the Federal Institute of Education, Science and Technology of Rondônia (IFRO), Brazil. The research was conducted based on the responses of 279 participants, evaluating dimensions such as cleanliness of the environment, temperature, variety and quality of the products provided. The main objective was to validate the hypothesis that the questions in the questionnaire are representative for measuring the dimensions proposed in the evaluation model. The results showed that the model has an excellent overall fit, with indices such as CFI (0.966) and RMSEA (0.044) within the recommended limits. The factor loadings of the latent dimensions and their indicators were statistically significant ($p < 0.001$), confirming the robustness of the model. In addition, the analyses showed the independence of the latent dimensions and the internal coherence of the indicators, reinforcing the validity of the instrument. This study not only validates the proposed model, but also provides support for improving the services

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evaluated, highlighting the applicability of SEM in similar contexts and opening possibilities for future research.

Keywords: Structural Equation Modeling (SEM). Service Quality Assessment. School Food Services. Instrument Validation. Public Educational Institutions.

RESUMO

Este artigo apresenta um estudo sobre a aplicação da Modelagem de Equações Estruturais (MEE) na avaliação da qualidade dos serviços prestados por um restaurante escolar do Instituto Federal de Educação, Ciência e Tecnologia de Rondônia (IFRO), Brasil. A pesquisa foi conduzida com base nas respostas de 279 participantes, avaliando dimensões como limpeza do ambiente, temperatura, variedade e qualidade dos produtos fornecidos. O objetivo principal foi validar a hipótese de que as questões do questionário são representativas para mensuração das dimensões propostas no modelo de avaliação. Os resultados demonstraram que o modelo apresenta excelente ajuste geral, com índices como CFI (0,966) e RMSEA (0,044) dentro dos limites recomendados. As cargas fatoriais das dimensões latentes e seus indicadores foram estatisticamente significativas ($p < 0{,}001$), confirmando a robustez do modelo. Além disso, as análises demonstraram a independência das dimensões latentes e a coerência interna dos indicadores, reforçando a validade do instrumento. Este estudo não apenas valida o modelo proposto, mas também fornece suporte para melhorar os serviços avaliados, destacando a aplicabilidade do SEM em contextos semelhantes e abrindo possibilidades para pesquisas futuras.

Palavras-chave: Modelagem de Equações Estruturais (MEE). Avaliação da Qualidade de Serviços. Serviços de Alimentação Escolar. Validação de Instrumentos. Instituições Públicas de Ensino.

RESUMEN

Este artículo presenta un estudio sobre la aplicación del Modelado de Ecuaciones Estructurales (SEM) en la evaluación de la calidad de los servicios prestados por un restaurante escolar en el Instituto Federal de Educación, Ciencia y Tecnología de Rondônia (IFRO), Brasil. La investigación se realizó con base en las respuestas de 279 participantes, evaluando dimensiones como la limpieza del ambiente, la temperatura, la variedad y la calidad de los productos ofrecidos. El objetivo principal fue validar la hipótesis de que las preguntas del cuestionario son representativas para medir las dimensiones propuestas en el modelo de evaluación. Los resultados mostraron que el modelo tiene un excelente ajuste general, con índices como CFI (0,966) y RMSEA (0,044) dentro de los límites recomendados. Las cargas factoriales de las dimensiones latentes y sus indicadores fueron estadísticamente significativas ($p < 0{,}001$), lo que confirma la robustez del modelo. Además, los análisis mostraron la independencia de las dimensiones latentes y la coherencia interna de los indicadores, reforzando la validez del instrumento. Este estudio no sólo valida el modelo propuesto, sino que también aporta apoyo para mejorar los servicios evaluados, destacando la aplicabilidad del SEM en contextos similares y abriendo posibilidades para futuras investigaciones.

Palabras clave: Modelos de Ecuaciones Estructurales (SEM). Evaluación de la Calidad del Servicio. Servicios de Alimentación Escolar. Validación de Instrumentos. Instituciones de Educación Pública.

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1 INTRODUCTION

Evaluating the quality of services in public and private organizations plays an essential role in ensuring efficiency and customer satisfaction. In the institutional context, such as university restaurants, measuring quality becomes even more relevant due to the direct impact on users and the need to comply with contractual and legal requirements. This study focuses on analyzing the quality of the services provided by a university restaurant, considering aspects such as taste, temperature, punctuality, hygiene, menu variety and service. To this end, a survey was carried out structured around six main dimensions, which assess both the characteristics of the services offered and the perception of users.

The purpose of the study is to validate a structural equation model (SEM) that allows the relationships between the dimensions evaluated and the respective indicators to be represented accurately and consistently. The use of SEM is justified by its ability to integrate measurement and causal analysis into a single statistical model, guaranteeing the validity and reliability of the inferences made. The questionnaire contained 26 questions, organized into dimensions related to different aspects of the service, such as food quality, cleanliness of the space and staff service. Each participant gave scores from 0 to 10 for the items evaluated, providing a broad and detailed database for the construction and validation of the model.

The main objective of this work is to verify the suitability of the proposed model, assessing whether the dimensions defined adequately represent the aspects observed and whether the indicators selected are capable of reliably capturing users' perceptions. In addition, it seeks to explore possible relationships between the dimensions evaluated and identify areas for improvement in the services offered. The study also contributes an efficient methodological approach, using advanced statistical techniques such as the lavaan package to implement the structural equation model and test its properties.

Throughout the analysis, the results of the overall fit of the model, the statistical significance of the indicators and the internal relationships between the dimensions and variables observed will be presented. Finally, it is hoped that the findings will not only validate the proposed model but also offer relevant insights for university restaurant management and for the implementation of more effective evaluation and continuous improvement practices. The methodological approach used could serve as a reference for similar studies, contributing to the evolution of research into service quality and institutional management.

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Structural Equation Modeling (SEM) has established itself as an efficient statistical tool for analyzing complex phenomena, enabling the investigation of relationships between latent and observable variables in various areas of knowledge. Recent studies have demonstrated its applicability in a variety of contexts, from public health to educational management, including topics such as vaccine hesitancy, job satisfaction, quality of services and urban infrastructure.

In the field of public health, Camargo et al. (2024) used SEM to examine the determinants of vaccine hesitancy against COVID-19 in Brazil. The study highlighted that conspiratorial beliefs were the main negative influence, while trust in health authorities acted as a protective factor. Misinformation and perceived stress also emerged as critical elements in increasing vaccine hesitancy, highlighting the importance of effective communication strategies to strengthen confidence in immunization and reduce barriers to vaccine uptake. In the same health context, Bogea et al. (2021) analyzed the relationship between obesity and inflammatory biomarkers in adolescents, demonstrating that excess weight is strongly associated with high levels of subclinical inflammation. Interestingly, dietary patterns and socioeconomic factors showed no significant associations, indicating that obesity may be the main driver of the inflammatory state in this population.

The influence of socioeconomic factors on health and human behavior was also highlighted by Mendez et al. (2023) who investigated the relationship between family economic conditions and childhood obesity in Argentina. The study found that better socioeconomic conditions facilitate the adoption of healthy habits, such as a balanced diet and regular physical activity, which in turn reduce the risk of childhood obesity. These findings reinforce the need for public policies that promote access to healthy food and opportunities for physical activity, especially among vulnerable families.

SEM has also been widely used to assess job satisfaction and its impact on workers' well-being. The study by Vieira et al. (2023) investigated the relationship between job dissatisfaction and depressive symptoms in Brazilian public school teachers. The results indicated that job dissatisfaction acts as a mediator between factors such as lifestyle and adiposity and the incidence of depressive symptoms. Teachers who were older or dissatisfied with their working conditions were more vulnerable to depression, while healthy habits had a protective effect. These findings highlight the need for improvements in working conditions and institutional support to promote teachers' mental health and, consequently, the quality of education.

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Still in the context of the public sector, Gomide et al. (2021) analyzed Brazilian bureaucrats' perceptions of state capacity and government performance. The research revealed that factors such as professionalization and technical skills directly impact the efficiency of public administration, while autonomy indirectly influences organizational effectiveness. On the other hand, organizational resources and interactions with non-state actors had no significant impact on perceived performance, suggesting that the training of civil servants may be a greater determinant of the quality of public service than the allocation of material resources.

The application of SEM in selection processes has also been explored as a way of improving fairness and accuracy in candidate selection. The study by (Maia and Lima, 2021), evaluated the candidate selection model at the State University of Ceará (UECE), identifying limitations in the approach based on Classical Test Theory (CTT). The implementation of a model based on SEM, complemented by Second Order Factor Analysis and Linear Regression, resulted in substantial improvements in discrimination between candidates, making the process more accurate and fairer. In addition, the adoption of this modern model has the potential to reduce drop-out and retention rates in undergraduate courses, improving academic efficiency.

Another field where SEM has proved to be a relevant tool is urban infrastructure and mobility. Romano et al. (2021) developed the User Perceived Cycle Path Quality Index (IQVCPU) in Brasilia, applying SEM to identify the main factors that influence the perceived quality of cycle paths. The results showed that the attractiveness of the route, accessibility and efficiency of the roads are determining factors in encouraging the use of bicycles as a means of transportation. In addition, barriers such as the disconnection of bike lanes and insecurity on stretches shared with motorized vehicles were pointed out as critical challenges to be overcome through effective public interventions.

The analysis of social support and its implications for different age groups has also been investigated using SEM. Jesus et al. (2022) examined factors associated with social support among the elderly, highlighting differences between genders. While women face challenges linked to greater longevity, widowhood and single-person households, men are more impacted by morbidities and less engagement in social activities. These findings reinforce the need for policies and programs that expand support networks for the elderly, preventing social isolation and promoting physical and mental well-being.

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In the field of nutrition and eating behavior, Mohammadi-Nasrabadi et al. (2020) applied SEM to study factors that influence the food consumption of Iranian women. The research used the Information, Motivation and Behavioral Skills Model (IMB) to understand how socioeconomic and psychological variables affect food choices. The results indicated that self-efficacy and self-regulation are directly associated with higher intake of healthy foods, while social support and educational level play important roles in modulating these habits. These findings reinforce the relevance of interventions that integrate nutritional education and behavioral strategies to promote more balanced diets.

Finally, the evaluation of professional satisfaction in the health sector has also been widely explored using SEM. Benevides et al. (2020) developed a model to analyze the satisfaction of doctors in the Mais Médicos Program (PMM) in Paraíba, highlighting factors such as the availability of medicines $\beta = 0.53$ and the infrastructure of health units $\beta = 0.39$ as key determinants. The study showed that technical and administrative support are key to retaining doctors in remote areas and suggested that investments in these areas could reduce turnover and strengthen primary care.

In this way, the studies analyzed demonstrate the versatility of Structural Equation Modeling as an analytical tool, applicable to a wide range of contexts. Whether in the analysis of public policies, the evaluation of health services, urban mobility or selection processes, SEM provides an in-depth understanding of the relationships between variables and supports evidence-based decision-making. This review reinforces the importance of expanding the application of SEM in new scenarios, seeking to further explore its potential in modeling complex phenomena and formulating effective interventions.

2 ABOUT STRUCTURAL EQUATIONS

Structural Equation Modeling (SEM) is a powerful and flexible statistical approach used in research in the social sciences, health and marketing, among others. SEM makes it possible to investigate complex relationships between observed and latent variables, integrating factor analysis and regression into a single statistical model. Due to its ability to simultaneously evaluate measurement and structural models, this technique stands out in the validation of theoretical constructs and in the investigation of causal relationships between variables, (Neves, 2018).

The development of SEM is rooted in multivariate statistical theory, combining methods such as confirmatory factor analysis (CFA) and multivariate linear regression. This

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integration allows researchers to represent relationships between observed variables (indicators) and latent variables (theoretical constructs that are not directly measurable). Structural models explore causal relationships between latent variables, while measurement models verify how these latent variables are operationalized through indicators (dos Santos Pereira, 2013).

A structural equation model consists of two main sub-models:

- Measurement Model: describes the relationship between observed and latent variables, which can be reflective (indicators reflect the construct) or formative (indicators define the construct).
- Structural Model: investigates causal relationships between latent variables, using path coefficients (β) to express the magnitude and direction of these relationships.

SEM uses multivariate regression to estimate relationships between variables. In simple linear regression, we have the relationship:

$$Y = \beta_0 + \beta_1 X + \epsilon, \qquad (1)$$

Where:

Y is the dependent variable

X is the independent variable

β_0 is the intercept, β_1 is the regression coefficient, and ϵ is the random error.

In SEM, this relationship expands to include multiple dependent and independent variables, as well as correlated errors (Ringle et al., 2014).

The correlation, expressed by the coefficient r, measures the strength and direction of the linear association between two variables. In SEM, correlations between measurement errors can indicate problems such as incorrect specification of the model or omitted variables.

Multivariate analysis plays a key role in SEM, especially in parameter estimation and model fitting. The main estimation methods include Maximum Likelihood (MLE), used in covariance-based modeling (CB-SEM) and Partial Least Squares (PLS), ideal for small samples or asymmetric data, with a focus on explanation and prediction.

Building a structural equation model requires specifying variables, hypotheses and relationships based on sound theory. Some fundamental steps include:

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1. Model Specification define latent and observed variables, as well as expected causal relationships.
2. Measurement validity: assess convergent validity $(\mathrm{AVE} > 0.50)$, discriminant validity (Fornell-Larcker criterion) and composite reliability $(\mathrm{CC} > 0.70)$.
3. Model fit: check indicators such as RMSEA (≤ 0.05), CFI (≥ 0.90) and TLI (≥ 0.90) to assess how well the model fits the data.
4. Structural evaluation: interpreting path coefficients (β) and coefficients of determination (R^2), which indicate the proportion of variance explained in dependent variables.

A generic structural equation model can be represented by the following equations, (i) Reflective Measurement Model:

$$x_i = \lambda_i \xi + \delta_i, \quad y_j = \lambda_j \eta + \epsilon_j, \qquad (2)$$

Where:

x_i e y_j are observed variables

ξ e η are latent variables, λ_I e λ_j are factor loadings

δ_i and ϵ_j represent measurement errors.

We also have the (ii) Structural Model:

$$\eta = \beta\eta + \Gamma\xi + \zeta, \qquad (3)$$

Where:

β is the matrix of coefficients between endogenous variables

Γ is the matrix of coefficients from exogenous to endogenous variables

ζ represents the error of the structural model.

These equations make it possible to simultaneously represent relationships between theoretical constructs and empirical data, making it possible to investigate complex hypotheses (Amorim et al., 2012).

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SEM has proved indispensable in various areas. In health, for example, it helps to validate measurement instruments and to understand factors that influence adherence to treatments. In marketing, it is widely used to assess consumer behavior and purchase intentions. The use of software such as (AMOS, LISREL, R Lavaan package) and SmartPLS facilitates the implementation and interpretation of models, expanding access to and use of this technique in different fields.

3 ABOUT THE MODEL

The proposed model is based on a study carried out to systematically evaluate the service contract signed between a university restaurant and the Federal Institute of Education, Science and Technology of Rondônia (IFRO), Brazil. This restaurant provides meals such as breakfast, lunch and dinner, as well as operating as a snack bar during class breaks, meeting the dietary needs of the academic community. Students regularly visit the site, and it is up to the contract supervisor to carry out periodic evaluations to ensure compliance with legal requirements and guarantee quality standards and customer satisfaction.

The survey, structured around 26 questions, uses an evaluation scale of 0 to 10 to measure the quality of the services provided. These questions are organized into six broad dimensions, covering relevant aspects of the restaurant's operation. Data collection aims to identify strengths and opportunities for improvement, allowing the tax authorities to base their decisions on reliable and up-to-date metrics, as well as promoting the continuous improvement of the services offered to the IFRO community.

The survey is structured into six dimensions, each made up of indicators that assess specific aspects of the services provided by the restaurant. The first dimension focuses on the characteristics of the snacks sold in the establishment, considering quality, taste, temperature and variety. The second dimension focuses on the evaluation of drinks, including the variety, temperature and quality of the juices and soft drinks sold by the

The third dimension analyzes criteria related to the punctuality, temperature and quality of the buffet offered to customers. The fourth dimension investigates aspects related to the taste, seasoning and variety of the lunch and dinner menu. The cleanliness and hygiene of the buffet area are the focus of the fifth dimension, while the sixth and final dimension assesses the service, cleanliness and uniforms of the staff responsible for the service.

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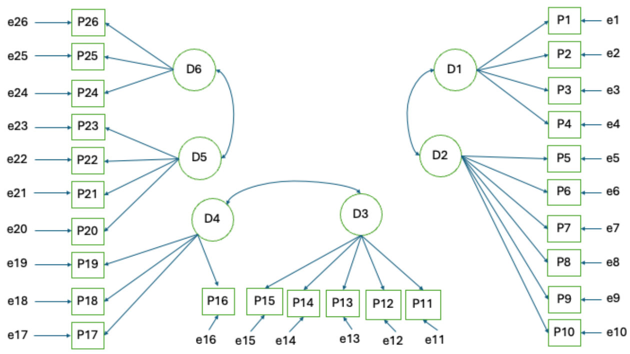
The aim of the study is to verify that the questionnaire used is capable of adequately capturing the dimensions proposed in the evaluation, ensuring that the questions represent the defined constructs. This validation process is based on the initial design of the path model presented in (figure 01), which serves as a reference for structuring the hypotheses and relationships observed.

Figure 1

Drawing the paths of the Hypothesis, where P_i represent the questions asked to customers and D_i represent the latent dimensions observed



Source: Authors

The survey data was organized as follows. The Dimension column identifies the main categories assessed (D1 to D6), while the Question column specifies the questions applied to the participants. In addition, columns Volunteer_1 to Volunteer_279 contain the answers provided by the participants, organized to allow a clear and systematic visualization of the assessments collected.

In the initial analysis of the data, it was identified that some columns had missing values, mainly concentrated in specific questions and answers. These values were treated to ensure the integrity of subsequent analyses. As an example, column Volunteer_1 has 6 missing values, while column Volunteer_276 has 9 missing values. This missing data will be taken into account in the cleaning process, using appropriate techniques to minimize possible impacts on the interpretation of the results, using the average of the component so as not to interfere with the final value of the result.

Thus, our model is represented as a direct dependency relationship between the observed variables and the corresponding latent variables, as well as a correlation between the latent variables, which can be seen in the equation 04:

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$$D_j = \beta_0 + \sum_{i}^{n}(x_i P_i + \epsilon_i) \qquad (4)$$

Where:

β_0 represents the intercept of the regression

x_i represents the model's fit coefficient;

P_i represents the value of the volunteer's answer to question i,

ϵ_i the sampling error linked to P_i, and when j=1 i ∈\{1,⋯,4\} , j=2 i ∈\{5,⋯,10\}, j=3 i ∈\{11,⋯,15\}, j=4 i ∈\{16,⋯,19\}, j=5 i ∈\{20,⋯,23\} and j=6 i ∈\{24,⋯,26\}

We also have the relationships between the latent variables that we modeled as shown in equation 5:

$$\begin{gathered} D_1 \leftrightarrow D2 \\ D_3 \leftrightarrow D4 \\ D_5 \leftrightarrow D5 \end{gathered} \qquad (5)$$

To confirm our hypothesis, we will use the **R software** to model and test the model, using its package **semPlot** to perform the path analysis and **lavaan** to test the model and make the necessary adjustments, as we will see in the next section.

4 DISCUSSION AND RESULTS

To begin our analysis, we processed the database, replacing missing values (since the questions were not compulsory) with the average of the values for that attribute. As well as using the lavaan package, we drew the first model as can be seen in the table 01:

Table 1

Initial Structural Equation Model

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```
model<-'
D1=~P1+P2+P3+P4
D2=~P5+P6+P7+P8+P9+P10
D3=~P11+P12+P13+P14+P15
D4=~P16+P17+P18+P19
D5=~P20+P21+P22+P23
D6=~P24+P25+P26
D1~~D2
D3~~D4
D5~~D6
'
```

Source: Authors

Next, we are going to test the model by adjusting it, as we can see in the table 02 and the results can be seen using the summary() function.

Table 2

Fitting the model to the processed data to present the result

```
adjustment <- sem(model, data = new_data_filled)
summary(adjustment, fit.measures = TRUE,
    standardized = TRUE)
```

Source: Authors

The overall fit of the model shows excellent results, as indicated by the fit indices analyzed, see table 03. The Comparative Fit Index (CFI) obtained a value of 0.966, which is considered excellent, since values above 0.90 indicate an adequate fit. Similarly, the Tucker-Lewis Index (TLI) showed a result of 0.961, reinforcing the quality of the model, since values close to 1 reflect a good fit.

Table 3

Overall Model Fit

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```
lavaan 0.6-19 ended normally after 54 iterations

Estimator                                 ML
Optimization method                       NLMINB
Number of model parameters                67

Number of observations                    1674

Model Test User Model:

Test statistic                            1223.471
Degrees of freedom                        284
P-value (Chi-square)                      0.000

Model Test Baseline Model:

Test statistic                            28184.917
Degrees of freedom                        325
P-value                                   0.000

User Model versus Baseline Model:
Comparative Fit Index (CFI)               0.966
Tucker-Lewis Index (TLI)                  0.961

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)             -48843.010
Loglikelihood unrestricted model (H1)     -48231.275
Akaike (AIC)                              97820.020
Bayesian (BIC)                            98183.359
Sample-size adjusted Bayesian (SABIC)
97970.509

Root Mean Square Error of Approximation:

RMSEA                                     0.044
90 Percent confidence interval - lower    0.042
90 Percent confidence interval - upper    0.047
P-value H_0: RMSEA <= 0.050               1.000
P-value H_0: RMSEA >= 0.080               0.000

Standardized Root Mean Square Residual:

SRMR                                      0.019

Parameter Estimates:

Standard errors                           Standard
Information                               Expected
Information saturated (h1) model          Structured
```

Source: Authors

The Root Mean Square Error of Approximation (RMSEA) also showed excellent performance, with a value of 0.044, below the limit of 0.05, which indicates an adequate fit. The 90% confidence interval, between 0.042 and 0.047, reinforces this conclusion. In addition, the p-value associated with the RMSEA, equal to 1.000, statistically confirms the adequacy of the model.

Another relevant index, the Standardized Root Mean Square Residual (SRMR), showed a value of 0.019, well below the limit of 0.08, which also reflects an excellent fit. Finally, the chi-squared statistic was 1223.471 with 284 degrees of freedom, accompanied by a p-value of 0.000. Although this result may indicate a need for refinement, it is common to observe such values in large samples, not compromising the overall conclusions, in which case the use of the χ^2/df statistic is recommended, which in this case has a value of 4.307782. According to (dos Santos Pereira, 2013), any value in the range of 2 to 5 is considered reasonable.

Based on these results, it can be concluded that the model has an excellent overall fit. The proposed relationships between latent and observed variables show consistency with the data, reinforcing the validity of the model for the purposes investigated.

The measurement model shows statistically significant factor loadings between all the latent dimensions (D1 to D6) and their respective indicators (P1 to P26), with p-values of less than 0.001, demonstrating the robustness of the associations, see table 04. These loadings show the quality of the model's fit and the consistency between the latent and observed variables.

Table 4

Latent Variables

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Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
D1 =~						
P1	1.000				0.750	0.771
P2	0.920	0.031	29.610	0.000	0.690	0.727
P3	1.253	0.036	35.034	0.000	0.940	0.864
P4	1.138	0.035	32.882	0.000	0.853	0.801
D2 =~						
P5	1.000				0.550	0.662
P6	1.216	0.045	27.194	0.000	0.669	0.733
P7	1.649	0.053	31.155	0.000	0.908	0.862
P8	1.728	0.052	33.321	0.000	0.951	0.941
P9	1.750	0.053	33.145	0.000	0.963	0.933
P10	1.093	0.054	20.312	0.000	0.602	0.529
D3 =~						
P11	1.000				0.923	0.796
P12	1.079	0.027	40.494	0.000	0.996	0.866
P13	1.182	0.028	42.732	0.000	1.091	0.902
P14	1.138	0.028	40.913	0.000	1.051	0.873
P15	0.828	0.031	26.588	0.000	0.765	0.621
D4 =~						
P16	1.000				0.733	0.793
P17	0.910	0.023	39.698	0.000	0.667	0.848
P18	1.058	0.024	43.442	0.000	0.776	0.905
P19	1.065	0.023	45.427	0.000	0.781	0.939
D5 =~						
P20	1.000				0.818	0.817
P21	0.965	0.034	28.442	0.000	0.789	0.657
P22	1.071	0.026	41.648	0.000	0.876	0.887
P23	1.122	0.027	40.822	0.000	0.918	0.870
D6 =~						
P24	1.000				0.767	0.642
P25	0.977	0.041	23.913	0.000	0.750	0.918
P26	0.883	0.035	25.085	0.000	0.677	0.742

Source: Authors

Dimension D1, representing salty snacks, stood out with indicators strongly linked to it, such as P1, with a factor loading of 0.771, and P3, with an even more expressive value of 0.864, indicating a strong relationship between these items and the dimension. In turn, dimension D2, related to drinks, showed a highly representative indicator, P8, with a loading of 0.941, while P10 had a lower contribution, with a loading of 0.529. In dimension D3, corresponding to the buffet, indicator P13 was the most significant, with a loading of 0.902, while P15 had a lower relative contribution, with a value of 0.621.

These results indicate that the indicators (or questions) are representative of the latent dimensions they are intended to measure. Higher factor loadings reflect indicators that are more representative and relevant to the dimension, while lower loadings indicate a lower relative contribution. This analysis reaffirms the validity of the measurement model, guaranteeing its adequacy in representing the relationships between the indicators and their respective latent dimensions.

The analysis of the covariances between the latent dimensions of the model (D1 to D6), see table 05 reveals very low values or values close to zero, indicating a lack of significant relationship between them. For example, the covariances between D1 and D2 were -0.000, while between D3 and D4 they were 0.000, reinforcing that there is no detectable relationship between these dimensions. This independence suggests that each dimension reflects different aspects of the services assessed, which contributes to the specificity of the measurements made.

Table 5

Covariances Analisys

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Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
D1 ~~						
D2	-0.000	0.011	-0.000	1.000	-0.000	-0.000
D3 ~~						
D4	0.000	0.018	0.000	1.000	0.000	0.000
D5 ~~						
D6	-0.000	0.017	-0.000	1.000	-0.000	-0.000
D1 ~~						
D3	0.000	0.019	0.000	1.000	0.000	0.000
D4	0.000	0.015	0.000	1.000	0.000	0.000
D5	-0.000	0.017	-0.000	1.000	-0.000	-0.000
D6	0.000	0.016	0.000	1.000	0.000	0.000
D2 ~~						
D3	-0.000	0.013	-0.000	1.000	-0.000	-0.000
D4	0.000	0.010	0.000	1.000	0.000	0.000
D5	-0.000	0.012	-0.000	1.000	-0.000	-0.000
D6	0.000	0.011	0.000	1.000	0.000	0.000
D3 ~~						
D5	-0.000	0.020	-0.000	1.000	-0.000	-0.000
D6	0.000	0.019	0.000	1.000	0.000	0.000
D4 ~~						
D5	-0.000	0.016	-0.000	1.000	-0.000	-0.000
D6	0.000	0.015	0.000	1.000	0.000	0.000

Source: Authors

About the correlations between indicators, some added associations between specific pairs helped to improve the model's fit. For example, indicators P5 and P6, belonging to the D2 dimension, showed a strong correlation of 0.507, while P8 and P9, also from D2, showed a moderate-high correlation of 0.505. In the D1 dimension, indicators P3 and P4 showed a moderate correlation of 0.328. These associations highlight the importance of considering specific relationships between indicators within the same dimension to better capture the structure of the data.

The results point to a model where the latent dimensions remain independent, while the indicators show correlations that reinforce the internal consistency of each dimension. This combination is essential to ensure that the model adequately captures both the specificity and the interrelationship between the elements measured.

The analysis of variances, see table 06, shows that the measurement errors, represented by the residual variances, are statistically significant $(p < 0.001)$ which indicates that the indicators are not perfectly explained by the latent dimensions with which they are associated. For example, indicator P1, belonging to dimension D1, has a residual variance of 0.406, which means that 59.4% of its variation is explained by the dimension. Indicator P8, from dimension D2, has a residual variance of 0.115, indicating that 88.5% of its variation is explained by the dimension. These results show that indicators with higher residual variances contribute relatively less to explaining the latent dimensions, which may indicate the need for adjustments or improvements to the model.

Table 6

Variances Analisys

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Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.P1	0.384	0.017	22.778	0.000	0.384	0.406
.P2	0.426	0.018	24.298	0.000	0.426	0.472
.P3	0.301	0.018	16.594	0.000	0.301	0.254
.P4	0.407	0.019	21.290	0.000	0.407	0.359
.P5	0.389	0.014	27.774	0.000	0.389	0.562
.P6	0.385	0.014	27.192	0.000	0.385	0.462
.P7	0.284	0.012	24.480	0.000	0.284	0.257
.P8	0.118	0.007	16.543	0.000	0.118	0.115
.P9	0.137	0.008	17.843	0.000	0.137	0.129
.P10	0.929	0.033	28.355	0.000	0.929	0.720
.P11	0.493	0.020	24.952	0.000	0.493	0.366
.P12	0.331	0.015	21.884	0.000	0.331	0.250
.P13	0.271	0.015	18.613	0.000	0.271	0.186
.P14	0.346	0.016	21.406	0.000	0.346	0.239
.P15	0.931	0.034	27.512	0.000	0.931	0.614
.P16	0.318	0.012	25.804	0.000	0.318	0.372
.P17	0.173	0.007	24.069	0.000	0.173	0.281
.P18	0.132	0.007	19.690	0.000	0.132	0.180
.P19	0.081	0.006	14.528	0.000	0.081	0.117
.P20	0.335	0.015	22.476	0.000	0.335	0.333
.P21	0.821	0.031	26.583	0.000	0.821	0.568
.P22	0.208	0.012	16.727	0.000	0.208	0.213
.P23	0.272	0.015	18.566	0.000	0.272	0.244
.P24	0.839	0.034	24.552	0.000	0.839	0.588
.P25	0.105	0.018	5.968	0.000	0.105	0.158
.P26	0.374	0.019	19.537	0.000	0.374	0.449
D1	0.562	0.032	17.760	0.000	1.000	1.000
D2	0.303	0.020	15.024	0.000	1.000	1.000
D3	0.852	0.044	19.193	0.000	1.000	1.000
D4	0.537	0.028	19.190	0.000	1.000	1.000
D5	0.670	0.034	19.671	0.000	1.000	1.000
D6	0.588	0.044	13.426	0.000	1.000	1.000

Source: Authors

As for the latent dimensions, their variances were set at 1.0 by default, a common practice in measurement models to ensure scalability and comparability between the dimensions. This adjustment allows for a consistent interpretation of the indicators in relation to their associated dimensions.

These findings highlight the importance of considering measurement errors when assessing the quality of the model. The presence of significant residual variances reinforces the need to identify possible adjustments to the indicators that will help improve the representativeness and overall fit of the model.

This model shows an excellent overall fit and strong evidence of validity for the latent dimensions and their indicators. The independence of the latent dimensions and the presence of residual variances in the indicators are consistent with a well-specified model.

The structure and configuration of the graph used to visualize the structural equation model were implemented using the semPlot package in R, see table 07, ensuring a clear and informative representation of the relationships between the latent and observed variables. The layout chosen, called cicle2, organizes the nodes in a circular arrangement, promoting visual symmetry and making it easier to understand the connections between the variables. In addition, the style adopted, lisrel, follows conventions used in Structural Equation Models (SEM), with directional arrows indicating the causal paths in the model.

Table 7

semPlot configuration

```
png("semPlot_modelo.png", width = 1600, height = 900, res = 300)
semPaths(ajuste, what = "std", whatLabels = "std", style = "lisrel",
  layout = "circle2", residuals = TRUE, edge.label.cex = 0.5,
```

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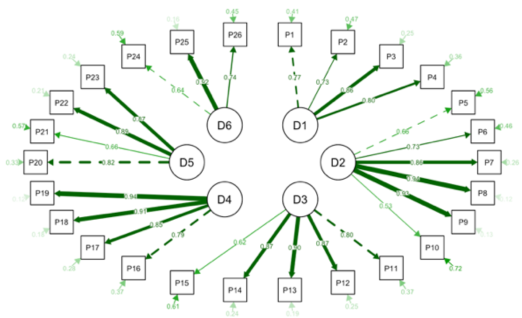
```
sizeMan = 4, sizeLat = 6, nCharNodes = 6, mar = c(5, 5, 5, 5))
```

Source: Authors

The edge labels (arrows), see figure 02 are configured to display the standardized coefficients, which indicate the strength of the relationships between the variables, while the residuals are included in the graph to represent the variability that is not explained by the latent factors. This approach ensures a more complete view of the model's fit.

Figure 2

Drawing of the analysis paths, where P_i represent the questions and D_i represent the latent dimensions observed



Source: Authors

The dimensions of the graph are well defined, clearly differentiating between the latent variables, represented by larger circles, and the observed variables, represented by smaller rectangles. This visual distinction allows a direct interpretation of the model's structure. Additional parameters, such as sizeMan and sizeLat, adjust the sizes of the rectangles and circles, while the mar parameter ensures adequate margins, preventing important elements from being cut off in the final graph.

These combined configurations provide a detailed and accessible visualization of the model, allowing the relationships between variables to be analyzed clearly and objectively, which is essential for interpreting and validating the results obtained.

The graph generated for the structural equation model shows relationships clearly represented by its edges, highlighting both causal connections and residual errors and covariances. The directional arrows are used to indicate causal relationships between latent and observed variables, as in the case of connections from D1 to indicators P1, P2, and so

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on, representing the associated factor loadings. The thickness of the edges plays an important role in interpretation: thicker arrows correspond to standardized coefficients of greater magnitude, suggesting stronger relationships, while thinner arrows indicate weaker relationships, helping to identify the most relevant connections in the model.

Residual errors are associated with each observed variable, such as e_1, e_2, among others. These elements capture the variability that is not explained by the latent dimensions, offering a more detailed view of the model's degree of fit and the specific contribution of each indicator.

This graphic structure allows for an intuitive visualization of the relationships between variables, facilitating both the understanding of causal connections and the identification of residual elements and covariances relevant to the model.

Analysis of the results of the structural equation model highlights the importance of factor loadings in interpreting the strength of the relationships between latent dimensions and observed variables. These loadings, represented by the arrows on the graph, provide a clear measure of the representativeness of the indicators in relation to the latent dimensions. Values close to 1 indicate that the indicators are well explained by the corresponding dimension, while lower values suggest that the indicators are less representative, which may point to the need for adjustments or revisions to the model.

The residual errors, represented by the circles associated with the observed variables, offer a complementary insight into the quality of the model's fit. High residual values indicate that a significant portion of the variance of the observed variables is not explained by the corresponding latent dimension, which can compromise the robustness of the model. On the other hand, low residual errors indicate that the latent dimension explains the observed variables well, reinforcing the validity and accuracy of the proposed relationships.

These results allow for a detailed evaluation of the model, highlighting the strengths and aspects that can be improved to enhance the consistency and representativeness of the data.

5 CONCLUSION

Based on the analysis of the results, the structural equation model showed a robust and adequate performance, being validated by means of various global fit indices and analysis of its internal properties. Key indicators such as the Comparative Fit Index (CFI = 0.966), the Tucker-Lewis Index (TLI = 0.961) and the Root Mean Square Error of

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Approximation (RMSEA = 0.044) were at excellent levels, according to the criteria established by the literature. These values indicate that the model fits the data well and that the proposed theoretical structure is consistent with the empirical observations. The analysis of the chi-square index adjusted by the degree of freedom $(\chi^2/df = 4.31)$ also reinforces the adequacy of the model, confirming the validity of the initial design.

The measurement model revealed statistically significant factor loadings for all the latent dimensions (D1 to D6) and their respective indicators, with values of $p < 0.001$. This shows that the indicators are representative of the proposed dimensions, with some factor loadings, such as P3 in D1 (0.864) and P8 in D2 (0.941), indicating particularly strong relationships. On the other hand, indicators with relatively lower factor loadings, such as P10 in D2 (0.529) and P15 in D3 (0.621), may suggest areas for refinement. These findings highlight both the robustness of the model and the need to pay attention to the less representative indicators, which can be adjusted or reformulated to improve their contribution to the latent dimensions.

The covariances analyzed between the latent dimensions were close to zero, indicating that the dimensions are essentially independent of each other. This independence reflects the specificity of each dimension in evaluating the different facets of the service provided, such as food quality, punctuality, cleanliness and service. This result is fundamental, as it reinforces the discriminant validity of the model, ensuring that each dimension captures unique and non-redundant aspects of the evaluation. However, within the dimensions, the correlations between indicators, such as between P8 and P9 in D2 (0.505), indicate that there are important connections that help explain the internal consistency of the dimensions.

Analysis of the residual variances revealed that some indicators have a significant portion of their variance not explained by the latent dimensions, as in the case of P10 in D2, whose residual variance was 0.929, indicating that 72% of its variability is not captured by the model. On the other hand, indicators such as P8 in D2 and P19 in D4 had very low residual variances (0.115 and 0.081, respectively), showing that they are well explained by their respective dimensions. This heterogeneity in the residual variances points to the need to revisit the less representative indicators, looking for ways to improve their integration into the latent dimensions.

The graph generated by the model, using the semPlot package, provided a clear and detailed visualization of the relationships between latent and observed variables. The circular layout and the use of directional arrows helped to highlight the causal connections and the magnitudes of the standardized coefficients, facilitating visual interpretation of the model. Elements such as the inclusion of residuals and adequate margins reinforced the precision and clarity of the graphical representation, ensuring that both global and local adjustments were well understood.

These results confirm the effectiveness of the proposed model in capturing the underlying relationships between the different aspects assessed. The independence of the dimensions, the robustness of the factor loadings and the overall fit indices show that the model is well-structured and suitable for the research objectives. However, the presence of higher residual variances in some indicators reinforces the need for continuous improvements in the questionnaire used, with a focus on revising or replacing less representative questions.

For future studies, we suggest exploring alternative models that could include new dimensions or indicators, expanding the scope of the evaluations. It would also be valuable to test the model on larger samples or in different institutional contexts, assessing its generalizability and robustness in different scenarios. In addition, longitudinal analyses could be incorporated to investigate the stability of the dimensions and indicators over time, providing deeper insights into the evolution of the services evaluated. These recommendations have the potential to further improve the validity and applicability of the model, contributing to the development of more accurate and comprehensive analysis tools.

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