Proposition of indicators for evaluation of Emergency Care Units

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Abstract
This study proposes the construction of indicators as a tool to evaluate how the services of an Emergency Care Unit (UPA) can be classified about the efficiency and quality of the services provided to its users. Based on metrics such as Length of Stay (LOS), Triage Cycle Time, Reception Service Time, among others, an unsupervised machine learning technique known as Exploratory Factor Analysis was used to obtain indicators. The results were obtained using the free software R. From the proposed indicators, it can be concluded that the higher the value found, generally, the worse the quality of the service provided. This indicates that the users remain in the Emergency Care Unit (UPA) for a long time.
Keywords: Emergency Care Unit; Indicator; Factor Analysis.

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Proposição de indicadores para avaliação de Unidades de Pronto Atendimento

Resumo

Este estudo propõe a construção de indicadores como ferramenta para avaliar como os serviços de uma Unidade de Pronto Atendimento (UPA) podem ser classificados quanto à eficiência e qualidade dos serviços prestados aos seus usuários. Com base em métricas como Tempo de Permanência (LOS), Tempo de Ciclo de Triagem, Tempo de Atendimento de Recepção, entre outras, foi utilizada uma técnica de aprendizado de máquina não supervisionada conhecida como Análise Fatorial Exploratória para obter os indicadores. Os resultados foram obtidos utilizando o *software* livre R. A partir dos indicadores propostos, pode-se concluir que quanto maior o valor encontrado, geralmente, pior é a qualidade do serviço prestado. Isso indica que os usuários permanecem por muito tempo na Unidade de Pronto Atendimento (UPA).

Palavras-chave: Unidade de Pronto Atendimento; Indicador; Análise Fatorial.

Propuesta de indicadores para la evaluación de las Unidades de Atención de Emergencia

Resumen

Este estudio propone la construcción de indicadores como una herramienta para evaluar cómo se pueden clasificar los servicios de una Unidad de Atención de Emergencia (UPA), en relación a la eficiencia y calidad de los servicios prestados a los usuarios. Con base en métricas como Tiempo de Permanencia (LOS), Tiempo de Ciclo de Triaje, Tiempo de Atendimiento de la Recepción, entre otros indicadores. Se utilizó una técnica de aprendizaje de máquina no supervisado, conocida como Análisis Factorial Exploratorio, para obtener los indicadores mencionados. Los resultados se obtuvieron utilizando el *software* libre R. Con los indicadores propuestos se puede concluir que cuanto mayor sea el valor encontrado, en general, peor será la calidad del servicio prestado. Esto indica que los usuarios permanecen en la Unidad de Atención de Emergencia (UPA) durante mucho tiempo.

Palabras clave: Unidad de Atención de Emergencia; Indicador; Análisis Factorial.

Introduction

The National Humanization Policy in Brazil is a comprehensive public policy that addresses the health work process, including assistance and management. It ensures the leading role of individuals and groups, covering the provision of services, care technologies, and the creation of secure and peaceful facilities that provide users with comfort and well-being. The health system faces a severe problem due to overcrowding of emergency services, which is further amplified by patients with minor ailments visiting these facilities. In response, urgent action is needed to plan work schedules, implement projects, and proposals aimed at providing efficient and dignified services that alleviate the pressure from increased demands. Therefore, humanization is crucial to reducing the effects that disrupt the service routine in the urgency and emergency network.

Leveraging the National Humanization Policy to support the quality of services offered in public Emergency Departments (ED) enables streamlining of medical care routines, enhancing the quality of services delivered to the population, and mitigating the likelihood of user dissatisfaction. Furthermore, it facilitates prioritizing the care of patients with graver conditions, leading to increased productivity and efficacy of specialized teams in the Unit, restructuring the workflows, and ensuring the provision of humane care.

The Lean Thinking research, in collaboration with the Ministry of Health of Brazil and the Fluminense Federal University, has been executed in emergency departments since 2020. This study aims to enforce a fresh service culture that aids in improving the standard and efficiency of services offered to Unified Health System (SUS) users in public emergency departments (ED). The research project's focus lies in enhancing critical patient care, curbing the standard period of the patient in the ED, reordering the constant flow of patients, and ensuring humane treatment is provided.

Amidst the challenge and impreciseness involved in appraising the quality of health systems, the literature suggests the indispensability of defining pertinent metric standards for evaluation employing reproducible and comparable indicators. These criteria are instrumental in objectively gauging data that might otherwise get lost in the subjectivity of individual judgments concerning the perceived quality of healthcare services received (Viola; Cordioli; Pedrotti; Iervolino; Bastos Neto; Almeida; Neves; Lottenberg, 2014). To this end, indicators are leveraged to assess the

classification of emergency departments' outcomes with respect to the efficacy and quality of the services extended to their users.

In this sense, the study proposes the construction of indicators as a tool to evaluate how the services of an Emergency Care Unit (UPA) can be classified about the efficiency and quality of the services provided to its users. Based on metrics such as Length of Stay (LOS), Triage Cycle Time, Reception Service Time, etc., an unsupervised machine learning technique known as Exploratory Factor Analysis was used to obtain indicators.

The selection of indicators hinges on the defined objective of the proposed study. The intended objective represents the anticipated solution to a predicament that a manager encounters in their everyday work routine. The indicators should direct the manager to undertake suitable actions toward achieving the desired result.

One of the challenges experienced by managers in the realm of emergency and urgent care is overcrowding of patients, which continues to be a prevalent issue in emergency departments. The implications of overcrowding provoke concern for both patients and healthcare practitioners, as the resultant tensions contribute to a drop in the quality standards of the service provided. Crowding's adverse effects comprise limited access to emergency services, delayed response to cardiac patients, escalated patient mortality, extended patient transport durations, inadequate pain control, assaults against staff from enraged patients, amplified expenses associated with care provision, and a decline in patient satisfaction with the treatment received (Hoot; Zhou; Jones; Aronsky, 2007).

Wang *et al*. (2017) identify how overcrowding is responsible for diminishing emergency department quality. The contributing factors include heightened ambulance movements and a heightened rate of patients departing from the emergency department without being attended, increased patient wait times, reduced level of patient satisfaction.

With this, there is a need to develop and evaluate indicators that consider the measurement of the time that the patient stays in the Emergency Care Units, from their cycle time of care at reception to time of care until discharge.
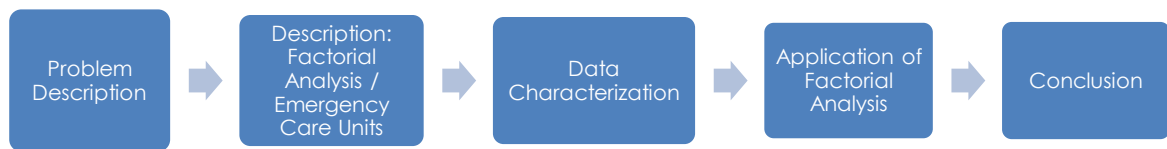
Methods

This section presents the classification of the research and the steps of the quantitative method for obtaining the outcomes.

Regarding the approach and nature, this research is categorized as being applied quantitative research, given its purpose to produce knowledge suitable for practical applications in solving explicit issues, with an emphasis on objectivity in the collection and analysis of numerical data, along with the use of statistical techniques in the analysis procedure (Garg, 2018).

As for the objectives, this study is characterized as exploratory research, in view of its aim to foster more familiarity and bring to light the problem, engaging in data analysis that encourages comprehension (Garg, 2018).

The steps of the proposed method are a description of the issue, characterization of the data, descriptive data analysis, application of Factor Analysis, and conclusion. Figure 1 illustrates these steps.

Figure 1 – Steps from the proposed method

Source: The authors (2024).

However, the Factor Analysis was presented before describing the steps of the proposed method, a contextualization of the machine learning tool used in the study.

Factor Analysis

Amaral (2023) examined and synthesized the primary findings and trends identified in studies employing the Factor Analysis method to derive indicators within the health sector. The bibliographic databases Scopus and Web of Science (WOS) were utilized for this analysis. Two principal applications of Factor Analysis were delineated in this study: validation of the measurement scale and validation of the questionnaire. Researchers employing the method to validate the measurement scale evaluated its appropriateness for capturing the intended construct. On the other hand, studies utilizing Factor Analysis to validate a questionnaire aimed to develop a questionnaire for indicator development and/or to furnish evidence regarding its structural reliability, validity, and precision.

In this sense, Factor Analysis has some objectives, such as reducing dimensionality, creating variables with the absence of multicollinearity and creating

performance indicators from the factors (Favero; Belfiore, 2019). This last objective of Factor Analysis is the purpose of this work.

According to Hair Junior, Black, Babin, Anderson and Tatham (2009), Factor Analysis can offer valuable insights to enhance decision-making processes. However, alongside its advantages of revealing relationships among intricate variables and reducing data dimensionality, Factor Analysis is also associated with certain limitations. These include challenges in result interpretation, and its inability to elucidate causal relationships.

The Factor Analysis model built from the correlation matrix is a model that linearly relates the standardized variables and the k common factors that, initially, are unknown. The equations of the model are given by:

$$Z_1 = L_{11} F_1 + L_{12} F_2 + \cdots + L_{1k} F_k$$
$$Z_2 = L_{21} F_1 + L_{22} F_2 + \cdots + L_{2k} F_k$$

$$\cdots$$

$$Z_p = L_{p1} F_1 + L_{p2} F_2 + \cdots + L_{pk} F_k$$

where: F_k - factor, also called latent variable (or unobservable variable); k – number of factors; p – number of variables; L – factor loading; Z_p - p-th standardized variable.

The calculation of factor loadings is performed from the eigenvalues and eigenvectors of the data correlation matrix.

However, analyzing only the correlations is not a sufficient guarantee to employ Factor Analysis. For this, the KMO (Kaiser-Meyer-Olkin) statistic, the anti-image, and the Bartlett sphericity test (Favero; Belfiore, 2019) are presented below.

- Kaiser-Meyer-Olkin (KMO) statistics compare simple correlations with partial correlations. The KMO value close to 0 indicates that the Factor Analysis may not be adequate (weak correlation between the variables). The closer the KMO to 1, the more suitable is the use of the model.

- Bartlett's Sphericity Test evaluates the hypothesis that the correlation matrix can be the identity matrix with a determinant equal to 1. If the correlation matrix is like the identity matrix, Factor Analysis should not be used (p-value must be less than 0.05).

- Anti-image, called Measure of Sampling Adequacy (MSA), obtained for each variable studied, is a way of getting evidence about the need to eliminate a specific variable from the model.

The factorial burden squared indicates what percentage of the variance of a variable is explained by a factor. The greater the factorial burden, the more significant the correlation of the variable with a given factor. A negative value indicates an inverse impact on the factor.

Exploratory Factor Analysis analyzes the pattern of correlations existing between variables and uses these patterns of correlations to group your variables into factors (or dimensions). The best-known method to create factors used in this study is Principal Component Analysis (PCA). This method is commonly used with an exploratory data analysis, as it does not require information or assumptions about the probability distribution of the data (Johnson; Wichern, 2007).

According to Hair Junior, Black, Babin, Anderson and Tatham (2009), the following criteria can be used to determine the number of factors:

- Latent root: all components with eigenvalues below 1 are discarded.
- Total explained variance: factors that guarantee x% of the total variance are selected, generally above 60%. Here, parsimony is emphasized (highest % of the variance with the least possible number of factors).
- Scree test: the latent roots are plotted against the number of factors in their order of extraction, and the shape of the resulting curve is used to assess the cut-off point.

Another possible step in using Factor Analysis is factor rotation. Factor rotations are intended to facilitate the interpretation of factors since the analyzed variables often present high factorial burdens in more than one factor. Factorial rotations can be of two orders: orthogonal (Varimax, for example) and oblique (Oblimin, for instance) (Johnson; Wichern, 2007).

The steps of the proposed method are presented in the following sections. The free software R was used to obtain the results (Wickham; Grolemundo, 2017).

Emergency Care Units

The Unified Health System (SUS) comprises diverse services that synergize to furnish medical assistance to the entirety of the Brazilian populace in need of care. These services, delineated across primary, secondary, and tertiary levels of care, are structured to enhance the organization of activities and resources within the system (São Paulo, [2013?]).

In accordance with the classification outlined by SUS, low-complexity healthcare is delivered through Basic Health Units (UBS) and Family Health Units (USF), whereas medium-complexity services are rendered via the hospital network, inclusive of Emergency Care Units (UPA). Conversely, high-complexity care is exclusively provided by hospitals (Kulicz; Uscocovich, 2021).

However, a significant portion of system users remain uninformed about the organizational structure of SUS services, leading to Emergency Care Units (UPA) being selected as the primary entry point into the healthcare system. This phenomenon has led to overcrowding within these units (Kulicz; Uscocovich, 2021).

As the focus of this research pertains to the UPA, it is imperative to underscore its definition and competencies. The UPA is categorized as a fixed pre-hospital component of intermediate complexity, positioning it between primary care and the hospital system. Consequently, its competencies include: a) provision of qualified and resolutive care for acute or chronic clinical conditions; b) conducting emergency medical consultations for minor cases; c) addressing care demands; d) administering first aid for surgical and trauma conditions, while maintaining clinical observation for up to 24 hours for diagnostic clarification or stabilization; e) referring patients with unresolved conditions after 24 hours to hospitals (Medeiros; Costa; Cardoso, 2021).

Another aspect addressed within the UPA is the enhancement of humanized emergency care, striving to incorporate practices such as attentive listening and respecting the patient's dignity, with the objective of fostering a positive experience during a health crisis (Rocha; Fernandes, 2016).

Emergency Care Units (UPA) are categorized into three types, delineating their characteristics based on size and addressing factors such as the served population, minimum physical area, daily medical care, minimum number of physicians per shift, and minimum number of observation beds (São Paulo, [2013?]). A summary of this information is provided in table 1.

Table 1 - Classification by size of UPA

Size	Population of the area covered (number of inhabitants)	Minimum physical area	Number of medical attendances in 24 hours	Minimum number of doctors per shift	Minimum number of observation beds
I	50,000 to 100,000	700 m^2	up to 150	2	7
II	100,001 to 200,000	1000 m^2	up to 300	4	11
III	200,001 to 300,000	1300 m^2	up to 450	6	15

Source: Rocha e Fernandes (2016).

In 2019, the country had approximately 657 Emergency Care Units, as reported by Comptroller General of the Union (CGU) (Brasil, 2020).

Data Characterization

In a given emergency care unit in Brazil, during February 2022, the following records were obtained: Patient identification, Service number, Reception cycle time, Triage cycle time, Service cycle time, Medication cycle time, Exam cycle time, Length of stay (LOS) with laboratory tests, Length of stay (LOS) without laboratory tests, Patient lead time, Time of care until discharge. Note that all measured times are in minutes.

Before starting the statistical analysis, recording errors were detected, such as negative time. These errors were eliminated from the research and the team of the Emergency Care Unit was instructed to correct the data. From these data, statistical measures were reported in table 2, where the highest average, median and standard deviation correspond to LOS With Laboratory Tests.

Table 2 – Statistical Measures

Variables	Average	Standard Deviation	Median
Medication Cycle Time	19.77	24.53	5.00
Exam Cycle Time	66.99	130.52	0.00
LOS With Laboratory Tests	166.92	138.98	112.00
Reception Cycle Time	1.47	0.72	1.00
Triage Cycle Time	3.54	2.09	3.00
Health Care Cycle Time	5.31	2.17	5.00
LOS Without Laboratory Tests	113.57	81.22	89.00
Patient Lead Time	82.72	74.54	63.00
Time of care until discharge	74.63	83.82	45.00

Source: The authors (2024).

Application of Factorial Analysis

Factor Analysis is used for data with high correlation in the data set. Mathematically, the objective of Factor Analysis is to explain the structure of variance or covariance/correlation of a data set. Then, Figure 2 illustrates the correlation of the variables studied.

Figure 2 – Correlation map of the variables studied
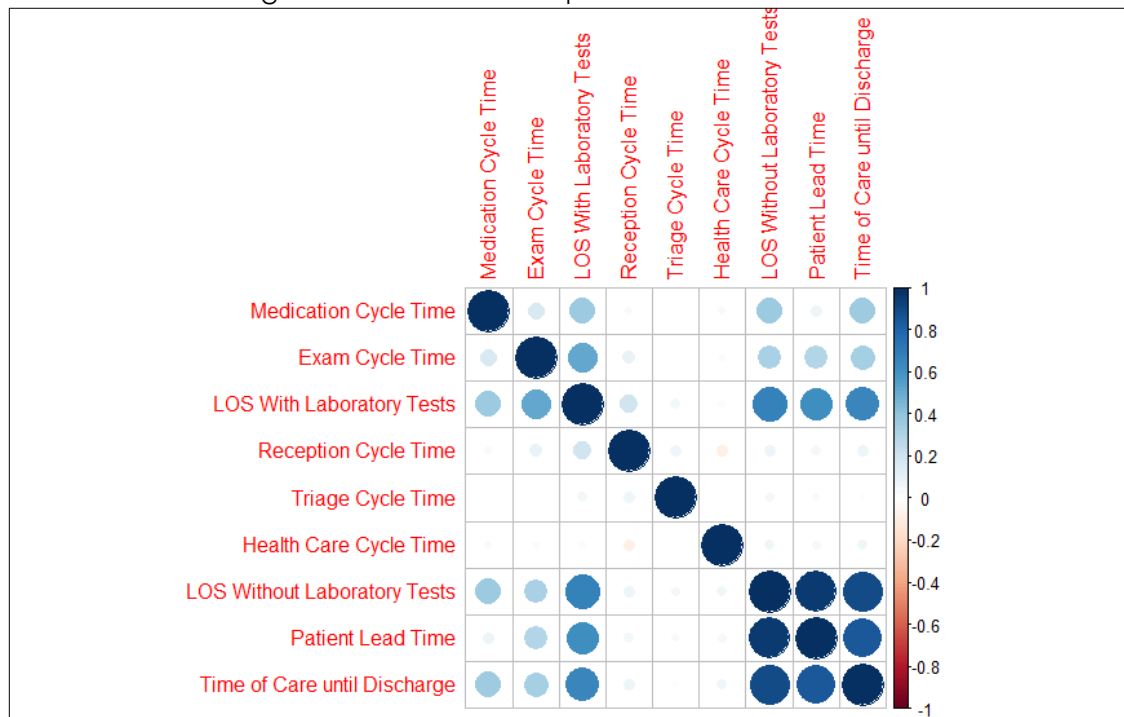
Source: The authors (2024).

It can be seen in Figure 2 that some variables have a high correlation, such as Medication cycle time, Exam cycle time, LOS without laboratory test, Patient lead time, Time of care until discharge, *etc*.

However, analyzing only the correlations is not a sufficient guarantee to employ Factor Analysis. For this, there are the KMO (Kaiser-Meyer-Olkin) statistic, the anti-image, and the Bartlett sphericity test.

In this study, Bartlett's sphericity test (1225,737, gl = 10, $p < 0.001$) and KMO (0.71) suggest interpretability of the correlation matrix, *i.e.*, the data matrix is liable for factoring.

Table 3 displays the Measure of Sampling Adequacy (MSA) of the variables used in the Factor Analysis (MSA > 0.60).

Table 3 – MSA of the variables used in the Factor Analysis (FA)

Variables used in the FA	MSA
Reception Cycle Time	0.66
Health Care Cycle Time	0.60
LOS without Laboratory Test	0.64
Patient Lead Time	0.70
Time of Care until Discharge	0.84

Source: The authors (2024).

Exploratory Factor Analysis analyzes the pattern of correlations existing between variables and uses these patterns of correlations to group your variables into factors (or dimensions). The best-known method to create factors used in this work is Principal Component Analysis (PCA). This method is commonly used with an exploratory analysis of the data because it does not require information or assumptions about the probability distribution of the data (Johnson; Wichern, 2007).

To determine the number of factors in this study, the latent root criterion (discard all components with eigenvalues below 1) and the explained total variance criterion were used. Table 4 presents the two factors with their respective % of variance explained. The two factors obtained explain 78% of the total variability of the data and eigenvalues greater than 1.

Table 4 – Eigenvalues and proportion of variance explained by the factor

Statistics	Factor 1	Factor 2
Eigenvalues loadings	2.81	1.08
Proportion Variance	0.56	0.22
Cumulative Variance	0.56	0.78

Source: The authors (2024).

This study did not perform factor rotation since the analyzed variables presented high factor loading in only one factor. The two factors and their respective factor loadings are in table 5.

Table 5 – Factor loading

Variables in Factor Analysis	Factor 1	Factor 2
Reception Cycle Time	0.11	**-0.73**
Health Care Cycle Time	0.09	**0.74**
LOS without Laboratory Test	**0.98**	0.01
Patient Lead Time	**0.97**	0.01
Time of Care until Discharge	**0.94**	0.00

Source: The authors (2024).

Figure 3 illustrates the factor loading and the % of explained variance in their factors (or dimensions).

Figure 3 – Factor loading and the % of variance explained in their factors
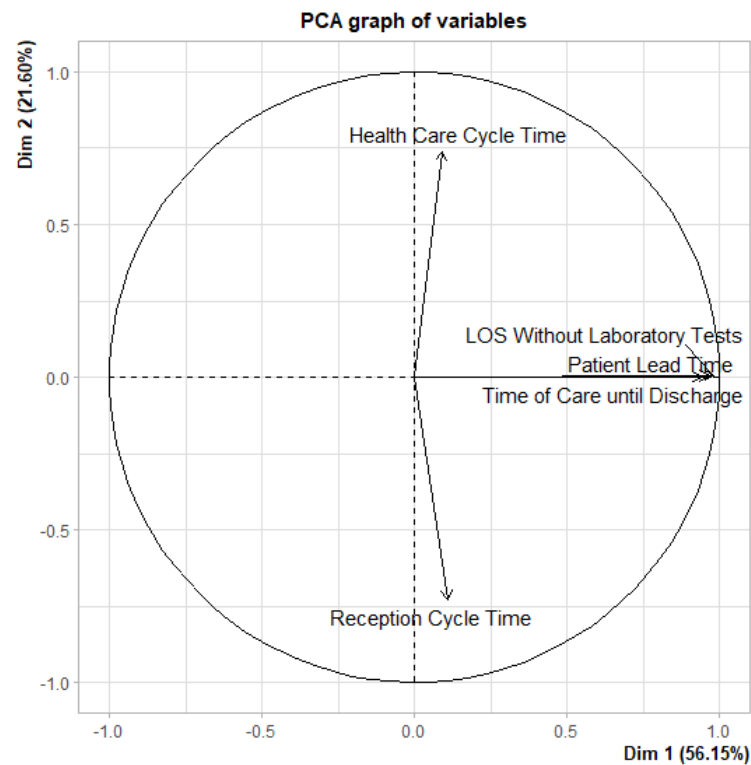
The proposed indicators for the studied Emergency Care Unit are calculated from the factors found. Table 6 presents the indicators and their respective calculations.

Table 6 – Indicators associated with original variables and calculations

Proposed Indicators	Original Variables	Calculation
Clinical Factor	LOS Without Laboratory Test; Length of Stay; Time of care until discharge	$Indicator_1$ = (0.98 x LOS without Laboratory test) + (0.97 x Length of Stay) + (0.94 x Time of care until discharge)
Cycle of Care	Reception Cycle Time; Health Care Cycle Time	$Indicator_2$ = (-0.73 x Reception Cycle Time) + (0.74 x Health Care Cycle Time)

Source: The authors (2024).

Table 6 shows that the "Reception Cycle Time" has an inverse impact on $Indicator_2$ "Cycle of Care".

It should be noted that higher indicator values mean poorer quality of service. This suggests that users of the system experience long waiting times in the Emergency

Care Unit, leading to patient dissatisfaction with the care received, overcrowding in the UPA and frustration on the part of the professionals involved. In this scenario, the proposed indicators serve as a guide for managers to implement operational changes in the functioning of the Emergency Care Unit, with a view to improving patient flow.

From this, it can be concluded that the objective of addressing the gap related to the absence of performance indicators based on the measured variables in the Emergency Care Units has been achieved.

Through the implementation of the proposed indicators, the following points for continuous improvement have been identified:

- Validation by managers to confirm the relevance of the obtained indicators, particularly in sensitive contexts like the healthcare sector. It is important to note that integrating multiple sources of evidence strengthens the interpretation and applicability of the derived indicators from this study.
- Training for focal points within the Emergency Care Unit on data manipulation and entry for the measured variables. Additionally, training on proper interpretation and utilization of results is necessary so they can effectively incorporate these indicators into decision-making processes or organizational strategies.
- Clear visual presentation of indicators using graphs to facilitate understanding and monitoring of results by various professional segments within the Emergency Care Unit.

Conclusion

In the healthcare sector, the decision to employ Factor Analysis for the development of performance indicators was grounded in the primary findings and trends identified in scientific research. Consequently, the anticipated outcomes were achieved.

The results obtained indicate that the objective of this study was successfully attained, which aimed to propose performance indicators for Emergency Care Units through the application of Factor Analysis. Two indicators were discerned in this investigation: Clinical Factor and Cycle of Care.

The proposed indicators, based on Factor Analysis, allow the evaluation of the quality and efficiency of the Emergency Care Unit to be conducted using several types of measurement time simultaneously. When the value of the proposed indicators

is large, the user spends a lot of time inside the Emergency Care Unit (UPA), which can generate dissatisfaction with the service provided, overcrowding in the UPA and frustration on the part of the professionals involved. Hence, Emergency Care Units can utilize this study as a tool to aid in managing patient flow.

Factor Analysis has significant value in creating performance indicators that are not directly observable. This statistical method allows for a more thorough interpretation of measured variables with diverse characteristics, leading to the development of indicators that effectively highlight these distinctions.

An inherent limitation of this study resides in the development of proposed indicators exclusively for a singular Emergency Care Unit (UPA). A more comprehensive and representative approach would entail applying these indicators across multiple UPAs, facilitating practical validation of their effectiveness and applicability in varied contexts. Replicating and validating these indicators in diverse Emergency Care Units could offer a more reliable assessment of their performance, allowing for broader comparisons between units and enhancing the robustness and generalizability of the findings.

As recommendation for forthcoming projects, it is advisable to develop an Action Plan aimed at empowering Emergency Care Unit (UPA) managers to oversee and monitor the outcomes of the proposed indicators. Additionally, it is crucial to ensure systemic validation of these indicators by UPA managers themselves. Furthermore, automating the recording of measured variables that constitute the performance indicators would be highly beneficial to mitigate potential typing errors that could affect the accuracy of the obtained results.

Acknowledgment

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