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ORIGINAL
Research article

Dashboard supported by business intelligence for decision making in the health sector*

Dashboard apoyado en inteligencia de negocios para toma de decisiones en el sector salud

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Abstract
This article aims to propose a dashboard supported by business intelligence (BI) as a support for strategic decision making in the Health Unit belonging to the University of Cauca with respect to patient morbidities, costs of care and investment in professionals. At the methodological level, CRISP-DM was used, defining six phases: business understanding, data understanding, data pre-processing, modeling, evaluation and finally deployment. As a result, it was found that the most common morbidities are: essential hypertension, dentin caries and excessive tooth attrition. Likewise, it was found that the specialty that demands the highest costs for the Health Unit is dentistry. Therefore, it is possible to indicate that the dashboard based on business intelligence is of vital importance for decision making in the context of preventive health with respect to morbidities by age range. In conclusion, the proposed

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dashboard serves as a support to the staff and administrative personnel of the Health Unit of the Universidad del Cauca in the design of contingency, promotion and prevention plans.
Keywords: Business Intelligence, Dashboard, Health, Morbidity, Promotion and Prevention

Resumen
Este artículo tiene como objetivo proponer un dashboard apoyado en inteligencia de negocios (BI) como soporte a la toma de decisiones estratégicas en la Unidad de Salud perteneciente a la Universidad del Cauca con respecto a las morbilidades de los pacientes, los costos de la atención y la inversión en los profesionales. A nivel metodológico, se hizo uso de CRISP-DM, definiendo seis fases a saber: comprensión del negocio, entendimiento de los datos, pre-procesamiento de los datos, modelamiento, evaluación y finalmente despliegue. Como resultado, se pudo evidenciar que las morbilidades que presentan una mayor ocurrencia son: hipertensión esencial, caries de la dentina y atrición excesiva de los dientes. Así mismo, se obtuvo que la especialidad que demanda mayores costos para la Unidad de Salud es la de odontología. Por lo anterior, es posible indicar que el dashboard basado en inteligencia de negocios es de vital importancia para la toma de decisiones en el marco de la salud preventiva con respecto a las morbilidades por rango etario. Como conclusión, el dashboard propuesto sirve de apoyo a los funcionarios y admistrativos de la Unidad de Salud de la Universidad del Cauca en el diseño de planes de contigencia, promoción y prevención.
Palabras Clave: Dashboard, Inteligencia De Negocios, Morbilidad, Promoción y Prevención, Salud

SUMMARY

Introduction

Every healthcare entity has the main objective of providing care to its members. Still, there are cases where chronic or high-cost diseases play a significant role in this sector, considering them as a challenge for health not only in primary care but also in the financial area of the entity. Since a patient with morbidity or multimorbidity requires continuous assistance and special care, this translates into high costs not only for the patient but also for the entity, resulting in a poor quality of life for the member due to their multimorbidity status (Barrio-Cortes et al., 2020). Figures indicate that a species is driven to extinction when its fertility rates are below 2.00% (López-Jiménez, 2008). According to data from the World Health Organization (WHO), population aging is a social phenomenon that is transforming economies and societies worldwide due to notable differences in birth rates (Alvarado-García & Salazar-Maya, 2014; Ordoñez-Erazo et al., 2022; Petretto et al., 2016). The phenomenon of multimorbidity in patients is observed, whereby few people are born, and many currently living, spanning different ages, suffer from different morbidities.

It is necessary to apply the advantages provided by Business Intelligence (BI) in healthcare provider organizations to analyze both patient morbidity or multimorbidity and the associated costs, supporting strategic decision-making in preventive health (Calzada & Abreu, 2009; García-Jiménez et al., 2021; Porras-Medrano et al., 2018; Viteri-Cevallos & Murillo-Párraga, 2021). In this regard, and the specific case of the University of Cauca, having its own Social Security System in Health (Health Unit), it requires having IT components that support decision-making regarding morbidity and allow streamlining internal processes, where business intelligence can contribute to addressing this problem. BI combines business analysis, data mining, information visualization, data analytics tools, and data infrastructure (Ahumada-Tello & Perusquia-Velasco, 2016; Tableau, 2019).

Similarly, BI can be understood as the set of methodologies, applications, and technologies that enable the integration, cleansing, and transformation of data from transactional and unstructured systems into structured information for decision-making purposes (Silva Peñafiel et al., 2019; Silva-Solano, 2017; Vanegas-Lago & Guerra-Cantero, 2013; Yang et al., 2020). Moreover, BI allows for developing competitiveness and positioning of a company based on knowledge management (Ahumada-Tello & Perusquia-Velasco, 2016; Guevara-Toscano et al., 2018).

To achieve the set objective, in the case of the Health Unit belonging to the University of Cauca, it is necessary to design a technological tool to display the morbidities of patients and the costs they represent in the healthcare unit through a dataset. Implementing a dashboard is required, as dashboards can graphically and concisely present metrics and relevant information from datasets with large amounts of data (Kenigsberg et al., 2022). They are considered one of the most comprehensive and user-friendly tools for the end-user. It is worth noting that a dashboard offers significant advantages such as versatility, understanding of information through charts and statistics, filters, and easy management for the developer. According to the above, the objective of this article was to propose an interactive dashboard supported by business intelligence as a support for strategic decision-making in the Health Unit belonging to the University of Cauca. The CRISP-DM methodology was used, which involves six phases: business understanding, data understanding, data preprocessing or preparation, data modeling, evaluation, and, finally, deployment. It is important to highlight that in the evaluation phase, in addition to reviewing the compliance with requirements by the development team, the functionalities were also verified through a focus group composed of stakeholders from the Health Unit belonging to the Universidad de Cauca. Finally, the proposed dashboard in this article serves as a reference to be extrapolated to other healthcare provider organizations and organizations in different application contexts.

Resolution scheme

1. Research problem

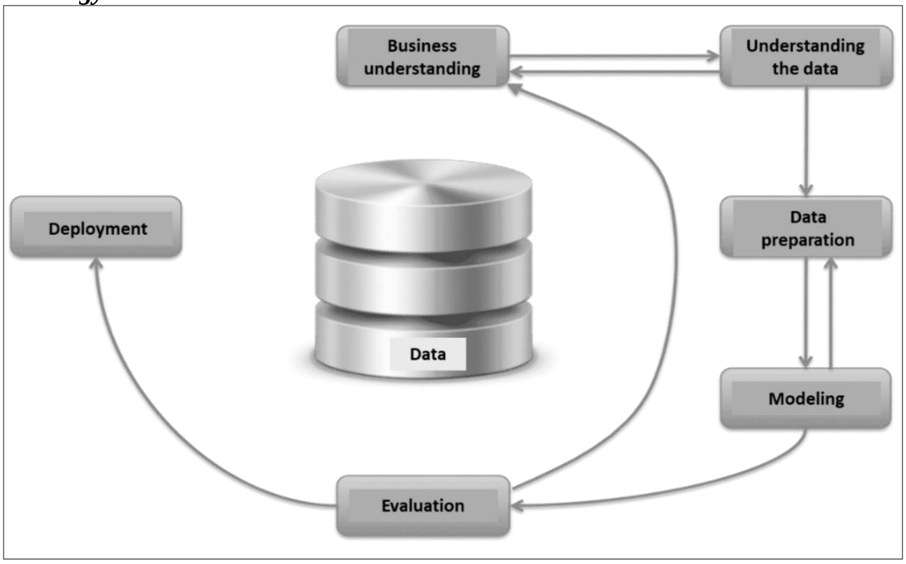
How to improve the analysis and visualization of morbidity data, multimorbidity and associated costs in patients of the Health Unit belonging to the University of Cauca?

2. Methods

For the design and implementation of the dashboard, CRISP-DM (Cross-Industry Standard Process for Data Mining) was chosen for this case, which is understood as a de facto standard and an industry-independent process model to apply data mining projects (Ayele, 2020; Cobos et al., 2010; Martinez-Plumed et al., 2021; Saltz, 2021; Schröer et al., 2021; Studer et al., 2021; Tripathi et al., 2021).

The model life cycle proposed by CRIPS-DM contains six phases with arrows indicating the most important dependencies: business understanding, data understanding, data preparation or pre-processing, data modeling, evaluation, and deployment (figure 1). The sequence does not necessarily have to be done in that order since many projects move back and forth according to particular needs (Abasova et al., 2021; Fernández, 2005; Kumar Singh et al., 2022; Marbán et al., 2008).

Figure 1. ***Methodology considered***



Source: Taken from (Alvarez-Gil, 2021).

The following are detailed descriptions of the 6 phases of the considered methodology.

Phase 1: Business Understanding. In this phase, the main idea of the data mining project must be established according to the business objectives. It includes evaluating the current business situation, setting project goals, and defining a project plan (Vallalta-Rueda, 2019). Within this phase, the first challenge was understanding the Health Unit's main objectives at the University of Cauca, as it is a complex institution with a large volume of information and a significant number of employees. The project analysts needed more time to evaluate the current business situation and assess the problems. It was important to set the objective of data mining from this point.

Phase 2: Data Understanding. In this phase, the data's nature, structure, distribution, and quality must be understood. Data capturing processes, exploration, and quality management should be executed, identifying possible problems and providing solutions (Vallalta-Rueda, 2019). Specifically, within this phase, the data and its collection were analyzed, identifying 1274 tables containing the information. These tables were analyzed and selected to extract the necessary information, uncovering issues such as missing or incorrectly entered data by the users of the system employed by the Health Unit at the University of Cauca.

Phase 3: Data Preparation. The goal of this phase is to obtain final data that can be used to establish the total amount of data to work with. It involves data cleaning and building a dataset that allows the execution of a data mining model (Vallalta-Rueda, 2019). In the present research, data selection was carried out, which required a significant time investment due to the number of database tables. This phase resulted in clean and error-free data, with structured and intact information to achieve the project's objectives, using basic office tools to generate filters and refinements.

Phase 4: Modeling. This phase focuses on building a model that fulfills the business objectives. It involves selecting the modeling technique, verifying the model's quality, building it, and fine-tuning it (Vallalta-Rueda, 2019). Specifically, in this phase, all the information from

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the dataset must be presented to the end user in an easily interpretable and interactive manner. Tools like Power BI and Google DataStudio are used to implement a dashboard, facilitating the evaluation of the constructed product.

Phase 5: Evaluation. This phase assesses the degree of alignment between the project and the modeling. The entire data mining process is reviewed, and adjustments can be made if necessary, or the project can proceed (Vallalta-Rueda, 2019). In this phase, the product evaluation was conducted through desktop and user testing to identify errors and potential improvements or adjustments to the dashboard. These evaluations aimed to verify the fulfillment of the initially defined functional requirements involving stakeholders from the Health Unit at the University of Cauca.

Phase 6: Deployment. The final phase involves deploying the results to end users and monitoring and maintaining the operational part (Vallalta-Rueda, 2019). The project was implemented and executed in this phase, considering the results obtained from the previous phases and the infrastructure available to the end users. The users only require a basic computer or mobile device with an internet connection and a web browser to run the application.

Considering the project's purpose, an analysis was conducted based on Business Intelligence (BI), combining business analysis, data mining, information visualization, data infrastructure, and best practices to support companies in making strategic data-driven decisions. From a practical perspective, implementing modern business intelligence involves having a comprehensive view of the organization's data. It uses this data to drive change, eliminate inefficiencies, and quickly adapt to market changes and demands (IBM, 2021).

The Health Unit at the University of Cauca has a database with over 1274 tables and a considerable number of records. Therefore, data selection from different tables and subsequent data cleaning were necessary. Tools like DataStudio were used to implement various reports. As a result of the Extract, Transform, Load (ETL) process, the Data Warehouse was loaded with 68047 records, including medical care for 2818 patients across 10 specialties and with 2322 patient diagnoses from 2018 to 2022. The data stored in the Data Warehouse was analyzed using the advantages provided by the Power BI exploitation tool, and the dashboard was implemented using reports generated from Google DataStudio. Allowed for functionalities such as data filtering, dynamic axis changes, and breakdown or display of information (drill-down and roll-up) segmented by available dimensions (patient diagnosis, age ranges, most demanded medical specialties, number of patient care based on the day of the week or year, among others).

3. Research results

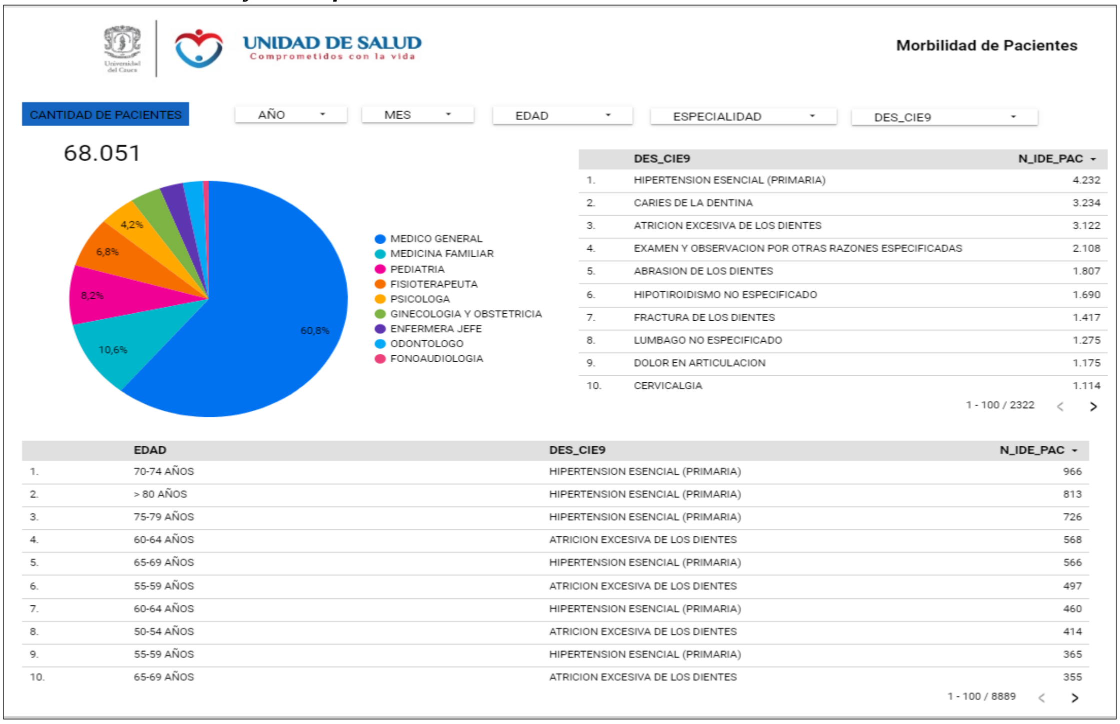
The implemented dashboard features three main views or interfaces that provide valuable information regarding patient morbidity, morbidity costs by age groups, and care costs for different morbidities at the University of Cauca Health Unit. Each of the dashboard views contains a set of figures and tables, as well as a set of filters that allow searches based on dates, specialties, and age groups.

Regarding the patient morbidity information, figure 2 presents one of the dashboard views showing the analysis of different medical care provided at the Health Unit over time. In this sense, Figure 2 displays a graph and two tables with the main diagnoses classified by physicians based on their professional judgment of the affiliated patients. Users can utilize filters by year, month, age, specialty, and diagnosis. Additionally, the dashboard presents the percentage of patients treated with their most representative diagnosis for each specialty. Figure 2 shows that the morbidities with the highest number of occurrences are essential hypertension, dentin caries, and excessive tooth attrition.

It should be noted that the dashboard can filter by patient age, where it is possible to relate the conditions and/or morbidities of patients with different age groups that have been grouped by five years (table 1). Thus, for example, table 1, extracted from Figure 2, shows how the highest number of consultations corresponds to the age ranges over 80, 75 to 79, and 70 to 74, with the morbidity of essential hypertension.

Similarly, Table 2 shows that the dashboard has an additional filter, which allows selecting the physician's specialty and relating it to the different diagnoses made to patients within that specialty. Provides the number of patients who consulted that specific specialty. For example, table 2 shows that the application results indicate that the Psychology specialty has 142 patient consultations, and the Pediatrics specialty has 273 consultations. The Dentistry specialty has a total of 78 patient consultations.

Figure 2. ***Patient morbidity view of the dashboard***



Fuente: elaboración propia.

Table 1. ***Dashboard filters by age group***

Id	Age range	Morbidity	Occurrences
1	70-74 years	Essential Hypertension (Primary)	966
2	> 80 years old	Essential Hypertension (Primary)	813
3	75-79 years old	Essential Hypertension (Primary)	726
4	60-64 years old	Excessive Tooth Atrition	568
5	65-69 years old	Essential Hypertension (Primary)	566
6	55-59 years old	Excessive Atrition of Teeth	497
7	60-64 years old	Essential Hypertension (Primary)	460
8	50-54 years	Excessive Atrition of Teeth	414
9	55-59 years old	Essential Hypertension (Primary)	365
10	65-69 years	Excessive Atrition of Teeth	355

Source: own elaboration.

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Table 2. ***Filters by dashboard specialty***

Specialty	Consult
Psychologist	142
Pediatrician	273
Dentist	78
General Practitioner	2000
Family Medicine	355
Gynecology and Obstetrics	120
Speech Therapy	22
Physical Therapist	228
Head Nurse	92

Source: own elaboration.

It is possible to determine that hypertension is the leading and most frequent diagnosis in the population for the General Medicine specialty. Similarly, figure 3 presents the dashboard view that involves the cost of morbidity by age ranges of patients within the Health Unit of the University of Cauca. It can be observed that, in terms of different morbidities, the age range of 70 to 74 years represents the highest cost for the Health Unit of the Universidad de Cauca.

The report shown in figure 3 covers information related to the sum of costs and percentages by diagnosis of diseases diagnosed by the age group of patients. These graphs generated by the dashboard allow observing which age ranges entail higher costs for the healthcare institution regarding different morbidities. They are relevant for decision-making by the management of the Health Unit since there are diagnoses that can be prevented and addressed through health promotion and maintenance programs to avoid them becoming more costly patients. For the Healthcare Providers (IPS), these expenses are covered by the contributions of other affiliates. It is possible to observe how hypertension corresponds to the most costly pathology.

Similarly, figure 4 presents the dashboard with the cost of patient care by specialty. Figure 4 shows the top 10 physicians who have attended the most consultations, along with the financial report associated with each of these professionals. The Dentistry specialty generates the highest revenue within the Health Unit. These and other patterns are extremely useful for IPS management to plan corrective and preventive actions in the healthcare field.

In order to evaluate compliance with the initial requirements defined for the dashboard, a focus group was formed, consisting of the dashboard developers, officials from the Health Unit, physicians, and executives from the department. In this focus group, the different functionalities provided by the dashboard views were presented, and the scope and fulfillment of each requirement were qualitatively and quantitatively reviewed, along with the projections that each dashboard view allows from the perspective of the focus group members. The review conducted in the focus group is presented in table 3.

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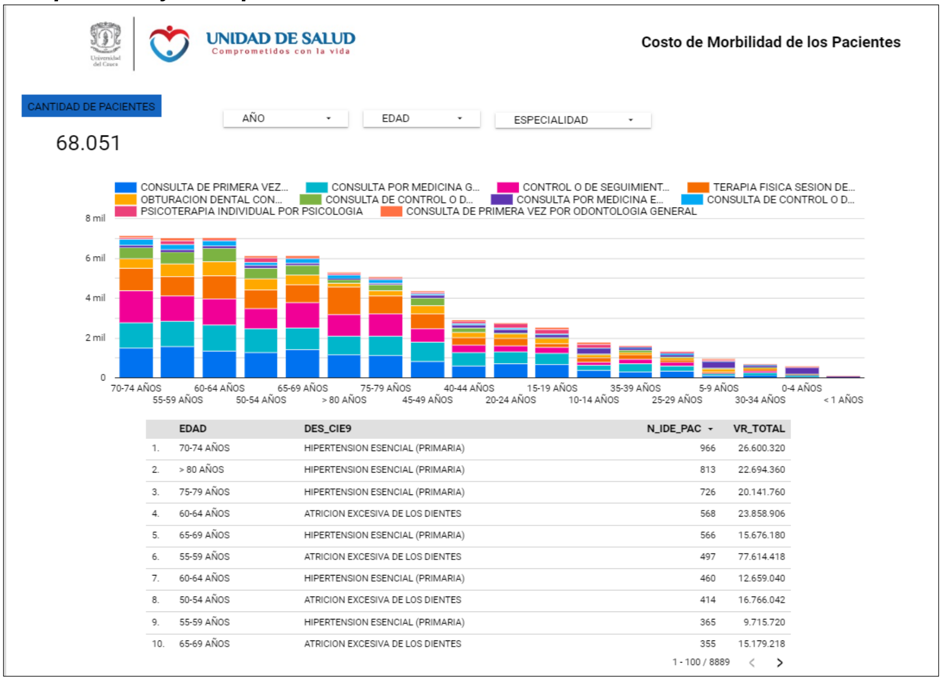
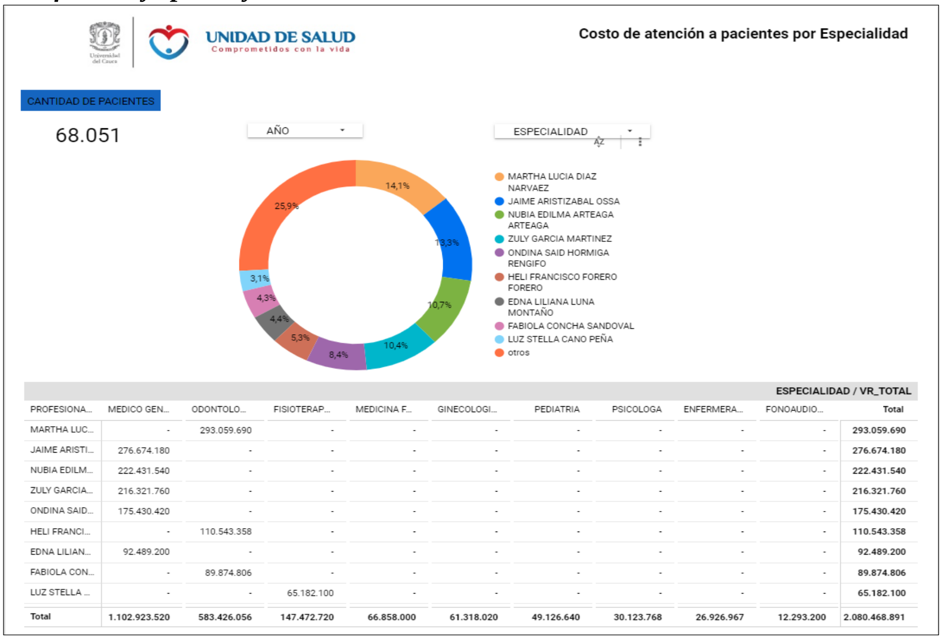
Figure 3. ***View of morbidity costs from dashboard***



Source: own elaboration.

Figure 4. ***View of costs by specialty on the dashboard***



Source: own elaboration.

Table 3. Verification of compliance with requirements

Requirement	Functionality obtained	Compliance with the requirement	Projections
R1. To present information regarding patient morbidities.	The first view of the dashboard shows the graphical and detailed relation of the different occurrences of the different morbidities in total and segmented by age group.	The requirement is fully met. The percentage of compliance is 100.00%.	This information allows the Health Unit to determine the morbidities on which preventive campaigns should be focused. It also allows the Health Unit to determine the

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			type and number of specialists that the Health Unit should increase in order to improve its service to the public.
R2. Display information regarding the cost of patient morbidities.		The requirement is fully met. The percentage of compliance is 100%.	
R3. Show the information corresponding to the cost demanded by the specialties.	The second view of the dashboard shows the cost demanded by different hospital groups by aggregating the morbidities.	The requirement is fully met. The percentage of compliance is 100%.	This information allows the Health Unit to plan health campaigns focused on a specific age range within the framework of preventive health.

Source: own elaboration.

Conclusions

The main results obtained from the proposed dashboard, which could be more evident when observing the databases of the Universidad de Cauca Health Unit, are highlighted. It was found that the morbidities with the highest occurrence are essential hypertension, dentin caries, and excessive tooth attrition. Additionally, it was determined that the age range of 70 to 74 years represents the highest cost to the Health Unit for various morbidities. Finally, it was also determined that the specialty that demands the highest costs for the Health Unit is dentistry. This information is vital for decision-making regarding preventive healthcare based on morbidity and age range.

Healthcare professionals can use business intelligence tools to address topics or studies of varying complexity to maximize data utilization and contribute to strategic decision-making within organizations. Thus, dashboard users can access refined, integrated, and consistent information simply and intuitively, generating new knowledge and gaining a more precise understanding of all areas of healthcare. The obtained results constitute the first steps in analyzing the information in the business and are available to the University of Cauca Health Unit. Based on the advantages of the implemented dashboard, the proposal detailed in this article can be extrapolated to different departments of the University.

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