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Maturity Model for Data Analytics in Health Institutions

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Abstract

Aware of the need for a data analytics model applicable in an environment of health institutions, which allows an efficient management of administrative processes, the analysis of disease behavior, a more accurate diagnosis, even processes of early detection of various pathologies . There is a tendency to apply data analytics techniques in health focused on care models focused on value and not on episode care, in order to increase benefits of historical data and support the resolution of possible complex pathologies. This research proposes a data analytics maturity model for health institutions called MMHEALTH, applicable to health institutions that need to improve their data analytics activities to obtain greater benefits, for this an analysis of some of the most important models is carried out. of existing maturity with an assessment applying the Likert scale, obtaining adequate characteristics of each model and that can be applied in the proposed new model, defined in a structure, and framed in six dimensions: Analytical Governance, Information Technologies, Culture, Data Analytics, Data Management , and Analytical Strategy, with which it is intended to implement formal data analytics processes in health institutions.

Keywords: Data analytics, maturity model, MMHEALTH model, health management.

I. CONTEXTUALIZATION

Data Analytic refers to quantitative and/or qualitative perspectives in order to obtain useful and important information from data. Consider techniques such as data extraction, to categorize them and determine possible relationships, trends or patterns of behavior. Currently, organizations of all types require a structuring of their data for their processing and obtaining information for effective decision making that allows optimizing the organization's business processes and improving performance. Depending on the type of organization and its business line, various data analytic techniques and models can be applied to help meet organizational objectives. It is essential to clearly determine requirements and data sources [1].

In the environment of health management, it is very necessary to use data analytics for several aspects, from improving administrative management, the study of the behavior of diseases in the population to accurately diagnosing, even pathologies that can currently be identified early to make timely and accurate interventions on some ailments [2]. Concomitantly, data analytics can be used to reduce costs of treatments, medical services, anticipate epidemics and improve efficiency in the management and administration of health facilities [2].

From the management of health care, direct benefits are known in risk analysis in orthopedic surgical interventions, in the guarantee of patient safety, in the management of scheduling of surgeries [5] [6]. In the administrative efficiency of the infrastructure and in the proper management of technology in health facilities, including optimization of maintenance of medical equipment[3] [4] [7].

Among the most notorious challenges in health data analytics are:

Systems Integration: Diverse IT solutions even within the same institution, with little or no compatibility, and a framework with low possibilities of integration between platforms and systems [8] [9].

Regulatory framework: In Latin America there is a limited definition of policies and strategies on the management and management of big data and its analytics, including in aspects of data privacy, ethical issues and legal issues in the analysis of data in health [8] [9][10].

Data management: There is a tendency of criteria in ensuring that many health systems are not efficient due to their limited ability to collect, analyze and make timely and effective decisions with patient data. Despite an expenditure on information management of almost 30% of their budgets, the problem still exists due to the decentralization and diversity of data sources [11] [12].

In summary, the challenges to be solved in eHealth are framed in the lack of integration of systems, the generation of regulatory frameworks, the almost zero exchange of information and with it the need for models and analytical methods adjusted to the reality of the sector [12].

For the generation of the Maturity Model of data analytics for health institutions MMHEALTH, a bibliographic review of the existing models is carried out, a valued comparison of their dimensions, their adaptability to health environments and their alignment with the requirements of institutions in the health sector.

II. MMHEALTH MATURITY MODEL

2.1 DEVELOPMENT OF THE MMHEALTH MODEL

It is considered the De Bruin methodology [14]. Thus the development of the MMHEALTH model is presented below phase by phase.

Scope

The proposed Model focuses on health organizations or facilities that belong to ecuador's national health system. Therefore, the dimensions and characteristics are aligned with the Ecuadorian regulations of this area and the organizational objectives of the health houses. The scope defines the processes/ areas/ department that generate and/ or process data in health institutions, either throughout the institution or in a specific area where their management is supported by processes linked to ETL processes.

Design

Comparison of models .- Current maturity models, created in the last five to six years, are analyzed as a reference, through a comparison the most appropriate components are extracted to be applied in the health sector. The following table lists the models analyzed.

Table 1 : *Maturity Models analyzed*

Codificación	Model	Reference	Year
BAModel	Business Analytics Maturity Model	http://www.diva-portal.se/smash/get/diva2:1332820/FULLTEXT01.pdf	2019
APModel	Analytics and Processes Maturiry Model	International Journal of Information Management	2018
IAMM	Industrial Analytics	https://papers.phmsociety.org/index.ph	2016

	Maturity Model	p/ijphm/article/download/2466/1429	
BDMM	Big Data Maturity Model	https://www.snaplogic.com/glossary/big-data-maturity-model-bdmm	2016
BDAMModel	Big Data and Analytics Maturity Model	http://icoci.cms.net.my/PROCEEDINGS/2017/Pdf_Version_Chap14e/PID117-613-620e.pdf	2017
SSAModel	Self-Service Analytics Maturity Model	https://www3.microstrategy.com/getmedia/77370952-e99e-4093-b607-76c3204f2c4e/TDWI-Self-Service-Maturity-Model-Guide.pdf	2017
BIAModel	Business Intelligence and Analytics Maturity Model	https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=3140412#page=228	2017

Source: Own elaboration

The following table presents the benchmarking between models with a Likert scale of 1 to 5, to measure the degree of agreement with the requirements of the health institution environment, where 1 = No concordance, 2 = low concordance, 3 = mean concordance, 4 = high concordance, 5 = total agreement, in relation to the following aspects:

Dimension: The objectivity of the dimensions of the model is evaluated, whether or not they are relevant to the improvement of data analytics activities.

Level: The quality scale in health institutions is measured in relation to data analytics activities.

Normative: Evaluates the instructions to improve data analytics processes.

Diagnosis: The mechanism and the report of results of the maturity analysis applied by the model to obtain the appropriate diagnosis on AD processes is evaluated.

Alignment: The relevance of the model in relation to the objectives of the project is evaluated.

Table 2: *Comparative Analysis of Maturity Models*

Model	Dimensions (15%)	Levels (20%)	Regulations (15%)	Diagnosis (20%)	Alignment (30%)	Compliance
BAModel	5	3	3	5	4	80%
APModel	5	5	3	3	5	84%
IAMM	5	3	4	4	3	76%
BDMM	5	5	3	4	5	88%
BDAMModel	5	5	3	3	4	80%
SSAModel	5	4	3	3	4	76%
BIAModel	4	4	3	5	5	84%

Source: Own elaboration

From this assessment, it is determined that the APModel, BDMM and BIAModel models are the most suitable for them to base the new model.

Structure of the Data Analytics Maturity Model

Initial meeting: The actors of the organization plan the type of information and the products to be required.

Diagnosis: With a scale criteria of 1-5, where 1 - Basic, 2 - Functional, 3 - Competitive, 4 - Differentiator and 5 - Continuous Improvement, the dimensions are evaluated.

Improvement: The weak points are determined to propose recommendations to be included in the improvement plans.

Artifacts: The resources, techniques and tools to execute the improvement plans are defined

Populate.- A comparative analysis of the dimensions of the models is carried out

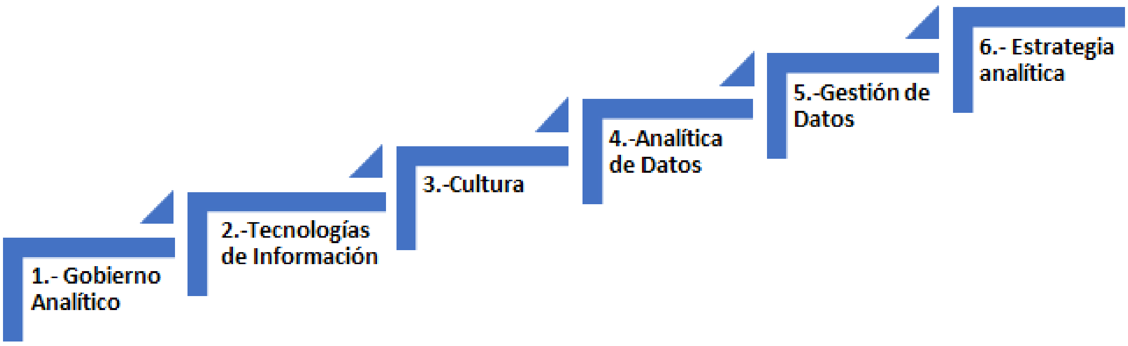
Table 3.- *Comparative analysis of the dimensions of the models*

Dimensions	BAModel	APModel	IAMM	BDMM	BDAMModel	SSAModel	BIAModel	Total
Information Technology	X	X	X	X	X	X		6
Data Analytics			X	X	X	X	X	5
Analytical governance	X	X		X	X	X		5
Culture	X			X	X		X	4
Data Management		X		X		X	X	4
Analytical strategy		X		X	X		X	4
Integrated Analytics			X		X			2
Analytical models		X						1
Personal	X			X				2
Open Standards			X					1
Operational Technology			X					1
Security & Compliance		X						1
Elicitación de Requisitos								0

Source: Own elaboration

This considers the following dimensions for the MMHEALTH maturity model. Analytical Governance, Information Technology, Culture, Data Analytics, Data Management, and Analytical Strategy.

Figure 1.- *Dimensions for the MMHEALTH maturity model.*



Source: Own elaboration

Validate .- For validation, the Delphi method is applied, defining as minimum characteristics of the experts the following: At least 5 years of experience, fourth level degree, working in health systems, in areas of management, administration or provision of health services, generating or managing data of the institution. At the level of applicability of the design, the maturity model is evaluated according to the instrument based on.

To reduce the threat to the validity of the statistical conclusion, the following aspects are considere. The questionnaires were answered with the same scale, in the same period, and by all stakeholders, without a change in the environment for the time the test was taken. The questionnaires were answered anonymously, however, there is an additional document signed by the actor as proof of application.

With regard to the internal threat to the validity, this study not considered the effect of history, maturity, and testing because it does not yet have the model implemented. Moreover, there is no threat of selection bias; the institution where the survey applies The participants have been selected at random, and not targeting a specific group, and all the players are interested in managing the analítica de datos y su aplicación en instituciones de salud. About the external threat to validity, there is no risk of interaction, because the sample is the total population of the institution to which the study is applied.

To validate the instrument, a reliability analysis of the survey was executed, obtaining a Cronbach's alpha coefficient of 0.846, which indicates that the data collection instrument has an acceptable reliability, thus determining the aspects and dimensions that affect data analysis in health institutions; he statistical treatment of the data was made using a spreadsheet, and Fisher's test was applied in the ANOVA and Tukey mean separation by analyzing the standard error and obtaining the percentage of good classification model; The corresponding exponential coefficients and confidence intervals were applied to the same 95% of reliability for ANOVA. Obtaining a level of significance less than 0.05, which presems to conclude that the MMHEALTH model is adequate to improve or implement data analytics activities in health institutions.

Deploy

For this phase, the model was validated in health institutions that have computer systems with a minimum level of analytics. It has been done through an anonymous virtual form generated on the Googleform platform. The organization's documents and products were collected that served as evidence to validate the answers provided by the respondents and to be evaluated. The answers and deliverables were evaluated and analyzed and then proceeded to complete the fields shown in the following questionnaires and thus define the levels of maturity by dimension. Determining a positive trend of applicability of the model in health institutions.

III. CONCLUSIONS

This paper presents a model of maturity of data analytics applied to health institutions, in order to identify gaps in the analytical environment of health institutions that lead to the reduction of these.

The MMHEALTH model is structured in 6 dimensions or phases with a specific order, Analytical Governance, Information Technology, Cultura, Data Analytics, Data Management and Analytical Strategy

The MMHEALTH Model aims to support the overcoming of the challenges of system integration; data privacy, as well as its ethical and legal management; and efficient data management.

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