

PRACTICAL FRAMEWORK FOR DATA MANAGEMENT AND IMPLEMENTATION OF DATA-DRIVEN HEALTHCARE AND BUSINESS INTELLIGENCE SOLUTIONS

Framework prático para gestão de dados e implementação de soluções de
inteligência de negócios e saúde orientadas por dados

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ABSTRACT

Introduction: Digital transformation and the incorporation of technologies such as big data, predictive analytics, and artificial intelligence have redefined healthcare management, directly impacting sustainability and quality of care within the Brazilian supplementary health system. In this context, the consolidation of robust data governance and analytics structures becomes essential to enhance care delivery, improve operational efficiency, and support regulatory and strategic decision-making.

Objective: To describe the development and implementation of a practical framework for deploying data-driven healthcare solutions based on Business Intelligence (BI), highlighting its contribution to management improvement and decision-making within the supplementary health system.

Methods: This study is a practical framework application grounded in the operational practices and accumulated experience of the Epidemiology and Health Information Department between 2022 and 2025. The framework was structured into six sequential stages: (1) business understanding and project planning; (2) data quality assessment and qualification; (3) data architecture definition and solution development; (4) technical validation and delivery; (5) monitoring and continuous improvement; and (6) process standardization and documentation. Implementation addressed clinical, administrative, and strategic demands.

Results: Implementation of the framework led to the development and maintenance of 240 institutional dashboards, of which 79 remain active, covering both clinical and administrative areas. During the study period, 582 structured data requests were addressed, expanding institutional analytical capacity, strengthening transparency, and supporting decisions related to quality of care, operational efficiency, and cost management.

Conclusion: The proposed framework demonstrated practical applicability as a tool to strengthen data governance within the supplementary health system, contributing to greater analytical maturity, evidence-informed regulatory support, and system sustainability. Its adoption may assist organizations in transitioning toward more efficient, transparent, and value-oriented care models.

Keywords: Data analytics; Data-driven; Data management; Healthcare.

RESUMO

Introdução: A transformação digital e a incorporação de tecnologias como big data, análise preditiva e inteligência artificial têm redefinido a gestão em saúde, com impacto direto na sustentabilidade e na qualidade da atenção na saúde suplementar. Nesse contexto, a consolidação de estruturas robustas de governança e análise de dados torna-se essencial para qualificar o cuidado, aumentar a eficiência assistencial e subsidiar decisões regulatórias e estratégicas.

Objetivo: Descrever o desenvolvimento e a aplicação de um framework prático para implementação de soluções em saúde baseadas em dados e inteligência de negócios (Business Intelligence – BI), destacando sua contribuição para o aprimoramento da gestão e da tomada de decisão no contexto da saúde suplementar.

Métodos: Este estudo é uma aplicação de um framework prático baseado nas práticas operacionais e na experiência acumulada do Departamento de Epidemiologia e Informações em Saúde entre 2022 e 2025. O framework foi estruturado em seis etapas sequenciais: (1) compreensão do negócio e planejamento do projeto; (2) avaliação e qualificação da qualidade dos dados; (3) definição da arquitetura de dados e desenvolvimento das soluções; (4) validação técnica e entrega; (5) monitoramento e melhoria contínua; e (6) padronização e documentação dos processos. A aplicação contemplou demandas assistenciais, administrativas e estratégicas.

Resultados: A implementação do framework resultou na criação e manutenção de 240 dashboards institucionais, dos quais 79 permanecem ativos, abrangendo áreas assistenciais e administrativas. No período analisado, foram atendidas 582 solicitações estruturadas de dados, ampliando a capacidade analítica institucional, fortalecendo a transparência e apoiando decisões relacionadas à qualidade assistencial, eficiência operacional e gestão de custos.

Conclusão: O framework proposto demonstrou aplicabilidade prática como instrumento de fortalecimento da governança de dados na saúde suplementar, contribuindo para maior maturidade analítica, suporte à regulação baseada em evidências e sustentabilidade do sistema. Sua adoção pode apoiar organizações na transição para modelos assistenciais mais eficientes, transparentes e orientados a valor.

Palavras-chave: Análise de dados; Ciência orientada por dados; Gestão de dados; Saúde.

INTRODUCTION

The digital transformation and the advancement of technologies, as big data, predictive analytics, and artificial intelligence, have significantly impacted healthcare management, particularly regarding information security and quality. This process requires organizations to adopt data-driven practices to improve care, optimize processes, and support decision-making. In this context, the use of tools to structure the implementation of solutions is essential to ensure alignment with client needs and to foster continuous improvement.

One of these tools is defined as a framework, a reference structure that organizes concepts, methods, and practices to support problem-solving within a specific domain. Unlike a theory or a model, it functions like a practical guide, facilitating communication, interpretation of phenomena, and decision-making. The literature presents different approaches to framework development, classifying them as conceptual, theoretical, hybrid, or practical ^{1,2}.

Practical frameworks stand out for consolidating knowledge built from experience rather than solely from formal theories ³. They are applicable tools in institutional contexts, such as process management or system development ².

Thus, the development of an institution-specific framework, adapted to its particularities, although not proof of complete integrity and coherence in the underlying process ⁴, may represent an innovation advantage. It enables the dissemination of practices from the professional context into the academic environment ², serving as a structured guide that directs data collection, analysis, and application, thereby promoting consistency and sustainability in implemented solutions.

OBJECTIVE

The study aims to describe the development and application of a practical framework for data management and the implementation of data-driven healthcare and Business Intelligence Solutions.

METHODS

This work is characterized as a practical framework application conducted in an institutional setting, with methodological features complemented by elements of an institutional experience report. The study systematically documents the development,

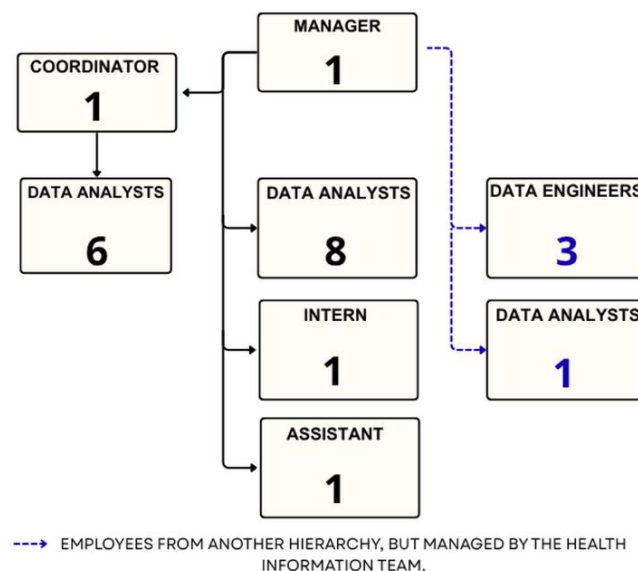
structuring, and application of the framework based on operational practices and real-world analytical demands.

For the purposes of this study, the term “data governance” is used in a pragmatic and operational sense, referring specifically to the set of practices, processes, and responsibilities adopted within the scope of the Epidemiology and Health Information Department to ensure data quality, consistency, accessibility, and appropriate use. The term does not imply a formal organization-wide governance model, but rather the governance mechanisms directly associated with the implementation and maintenance of the proposed analytical solutions.

The Health Information Department - Epidemiology, under the Health Economics Directorate, is structured to serve as a reference for the integrated management of data volume across all units that comprise Einstein’s healthcare services. In 2025, the team includes a manager who defines priorities and identifies opportunities for action; a coordinator responsible for operationalizing and monitoring deliverables; 15 data analysts, 3 data engineers, 1 intern, and 1 research assistant, each responsible for specific thematic areas (Figure 1).

Figure 1: Organizational chart of the Health Information Department - Epidemiology.

ORGANIZATIONAL CHART – HEALTH INFORMATION



Through a collaborative effort with the analysts, the processes and methods used in the projects were consolidated based on observation and critical analysis of historical

practices. From this, a draft was developed and validated with leadership, resulting in a practical framework composed of six stages: (1) Business understanding and project planning; (2) Data quality; (3) Data architecture and development; (4) Validation and delivery; (5) Improvements; (6) Documentation.

Stage 1: Business understanding and project planning

In this stage, the demand is identified, either through a formal request or by recognizing opportunities during meetings. The needs and challenges are then mapped with the goal of transforming data into value-driven strategies for the client side.

Next, a business understanding meeting is scheduled so that the client can describe the workflow in detail, outlining the main objectives and highlighting any inconsistencies in the current process, if already identified by the area. With this information gathered, project planning begins, during which tasks are organized in a shared board that allows visualization and prioritization of all demands, including scope definition, task allocation, timelines, and resource assignment.

The time required for the business understanding and project planning phase depends on the complexity of the demand, client availability, data source, and prioritization defined by the lead, with an estimated completion time ranging from one to three weeks ⁵.

Stage 2: Data Quality

In this stage, the existence of data in electronic systems is verified, their storage locations are identified, and their quality is assessed. Although the terms “data quality” or “information quality” still lack consensus regarding evaluation criteria ⁶, nine dimensions have been proposed to assess the quality of health information systems: (1) Accessibility, (2) Clarity, (3) Coverage, (4) Completeness, (5) Reliability, (6) Consistency, (7) Non-duplication, (8) Timeliness, and (9) Validity.

To ensure data quality, the first step is to verify the existence and accessibility of the data, identifying ease of handling, clarity of rules, and required security levels. Next, a sample is extracted to assess: clarity, records that are concise, didactic, and unambiguous; coverage, existence of the data; completeness, non-null records; reliability, degree of agreement among data; consistency, coherent and non-contradictory values; non-duplication, uniqueness of records; timeliness, availability of

updated information according to client needs; and validity, standardized values consistent with what is intended to be measured.

Finally, the effort required to correct any deficiencies is estimated, and, when necessary, the requesting department is advised on process adjustments and the reinforcement of proper data entry workflows within the system.

Stage 3: Data architecture and development

The process begins with ETL (Extract, Transform, and Load) ^{7,8}. In this stage, tools such as SQL, Python, R, or KNIME are employed. During the extraction phase, queries or workflows are executed to transfer information from the source system to the target repository. In the transformation phase, data are cleaned, standardized, and complemented according to the data quality dimensions described in Step 2 ⁶. In the loading phase, a standardized procedure is implemented to automate the process and ensure that data updates remain consistent and reliable, in accordance with the system's information governance guidelines.

Once the final table is established, a visual solution is developed. This may take the form of presentations, analytical tables, or, in more complex and robust projects, interactive dashboards using business intelligence (BI) tools. The structure is designed following best practices in dimensional modeling, linking the main fact table to complementary dimensions (e.g., calendar, time, location), validating relationships (with cardinality adjustments when necessary), and creating formulas to generate metrics. In addition, themes, charts, and filters are selected, and a glossary is implemented to ensure proper documentation.

In this final phase, the solution is first deployed to the report server within the testing environment, where it is validated by the requesting team. After approval, the dashboard is migrated to the production environment, adjusted for real-use conditions, and configured with the appropriate access control rules, ensuring that each user has permissions consistent with their role.

Stage 4: Validation and delivery

In this stage, the main objective is to verify whether the data accurately reflects the business reality. To achieve this, direct collaboration with the requesting department is essential, as it often maintains some form of parallel monitoring (manual or intuitive), allowing for comparison between the results and the control reference ⁹.

When the data produced by the solution aligns with the department's reality, the tool gains credibility and becomes a more reliable support for decision-making. If discrepancies arise between the processed data and the department's control records, these differences are thoroughly investigated to identify their causes. Only after resolving such divergences and reaching consensus between the parties, the final delivery is formalized and user training conducted, ensuring that users can correctly interpret and utilize the tool.

Stage 5: Improvements

During this stage, continuous monitoring of indicators and implemented solutions is carried out, with the main objectives of correcting identified issues and implementing progressive improvements. These actions are guided both by users' direct perceptions, captured through feedback and everyday interactions ¹⁰, and by a technical analysis of the solution conducted by the responsible team, which includes verifying data loads and assessing performance in terms of execution time and resource consumption.

In addition to this work, when necessary, the team may adapt the structure of the source data and actively optimize the code. This combination of qualitative and quantitative inputs enables more precise adjustments, making the tool more intuitive and better aligned with operational needs.

Stage 6: Documentation

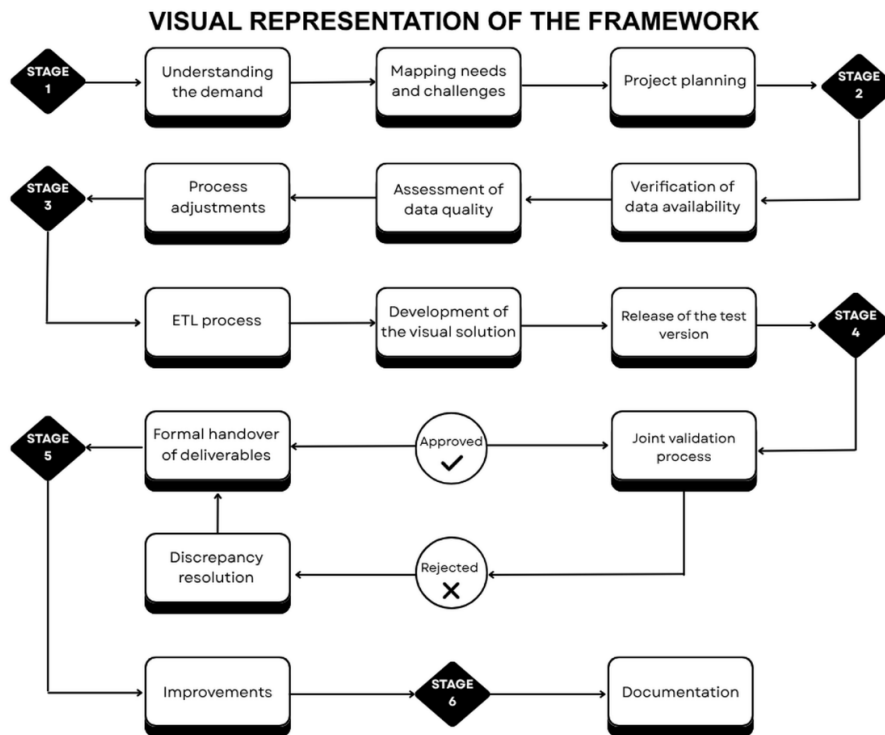
In this stage, the project is thoroughly documented. Although it is a relatively recent practice, documentation has become a key element for the success of projects. It consists of the systematic recording of relevant information, from the needs that gave rise to the solution to the initial requirements aligned with clients. In addition, it includes the identification of the main stakeholders, the beneficiary areas, detailed technical specifications, and the indicators developed to measure performance. Another essential aspect of this practice is the organized maintenance of historical files, which enables comprehensive monitoring and tracking of the project's evolution.

A well-structured documentation process also facilitates project maintenance, as new team members can quickly and accurately familiarize themselves with the context, reducing the adaptation period. Another important advantage is the reduction of the risk known as the "Bus Factor" ¹¹, in which the sudden departure of a key team member could jeopardize project continuity and the preservation of organizational knowledge.

RESULTS

As a result of the stages described above, a visual representation (Figure 2) of the framework for implementing healthcare solutions is presented.

Figure 2: Visual representation of the framework derived from the implemented stages.



According to the area's documentation, the implementation of the framework stages enabled the development of 240 dashboards, of which 79 remain active based on client demand. These dashboards cover a wide range of clinical and administrative areas. In addition, 582 data requests were fulfilled, including volume extractions, descriptive analyses, and datasets for scientific research, between 2022 and the first half of 2025 (Table 1). Among the various requests and dashboards developed, some cases stand out for having followed all stages of the framework, from the initial needs assessment to the final delivery. These cases were selected for having received relevant accreditations and awards, as well as for generating significant value for the areas involved.

Table 1. Number of data requests fulfilled per year in the Health Information -

Year	Number of requests
2025.1	105
2024	187
2023	129
2022	161

Epidemiology division

Case Reports

Case 1: Outpatient Rehabilitation Dashboard

An analytical dashboard was developed for the Outpatient Rehabilitation service, which provides multidisciplinary care across five units with different levels of complexity and clinical specialties. The solution consolidated data extracted from the electronic health record and enabled the monitoring of key clinical and operational indicators, including therapeutic plan adherence, Functional Independence Measure (FIM), rehabilitation diagnostic profile, discharge indicators (treatment dropout and return-to-work status), and performance in the Six-Minute Walk Test (6MWT).

These indicators supported standardized monitoring of both patient outcomes and service performance, which had previously been fragmented across multiple systems and manual reports.

Observed benefits and operational impacts included automated and efficient monitoring of rehabilitation indicators, with improvements in data completeness and standardization within the electronic health record. The availability of structured and integrated information supported clinical and managerial decision-making, reduced the time required to compile data for meetings, and enabled, for the first time, a consolidated view of the diagnostic profile of patients undergoing rehabilitation.

The development of these indicators also enabled a detailed audit of clinical records, leading to targeted actions to correct inconsistencies and standardize data entry practices. As a result, the team is now able to monitor data completeness and data quality in real time. Furthermore, improved access to reliable and comparable information supported the evaluation of care delivery, facilitated actions to standardize and improve

rehabilitation workflows, and enabled more effective planning of care pathways, allocation of human resources, and continuous monitoring of patient outcomes across units.

Case 2: Nutrition Department Dashboard

An analytical dashboard was developed for the Nutrition Department, with a focus on automating the collection and analysis of data related to enteral, parenteral, and oral nutrition therapy for inpatients at the Morumbi Unit. The solution integrated data from the Cerner Millennium electronic health record and enabled real-time monitoring of key clinical and operational indicators, replacing a previously manual and fragmented workflow based on spreadsheets.

The dashboard consolidated indicators related to measured weight, discharge guidance, number of patients assisted per day, indirect calorimetry and bioimpedance examinations, device assessments, infused volume, caloric and protein intake, and events of nasoenteral tube loss.

The implementation generated measurable clinical and operational benefits. Automation reduced approximately 160 hours of manual monitoring work, allowing the team to redirect efforts from data collection and spreadsheet maintenance toward action planning and care improvement initiatives.

Real-time data availability contributed to a 26% improvement in the adequacy of weight recording among patients receiving nutritional therapy, as continuous monitoring enabled daily follow-up and active reinforcement of documentation practices by the nutrition team. Additionally, improved visibility of indirect calorimetry and bioimpedance examination results supported managerial decision-making regarding service expansion, with an estimated potential annual revenue increase of approximately BRL 231,000.

Case 3: Childbirth Dashboard

In the childbirth project, a volumetric comparison was conducted between data extracted from the electronic health record and information recorded in a manually completed childbirth logbook. This analysis revealed that essential clinical and operational information, such as type of delivery, physician, breastfeeding within the first hour of life, and, in some cases, even date of birth, was frequently missing from the system due to the optional nature of these fields.

Retrospective data entry proved unfeasible given the continuous operational demands of the area, compromising future automation and analytical initiatives. Based on the discrepancies identified, joint meetings were held between clinical, operational, and data teams to align strategies, resulting in the redesign of the childbirth registration form and the adoption of mandatory completion rules for essential fields during data entry.

With the new standardized registration structure, data began to be systematically captured within the electronic system and automatically extracted into analytical datasets, enabling the generation of reliable indicators to support strategic decision-making in the childbirth area.

Key indicators consolidated through the dashboard included total delivery volume stratified by delivery type (vaginal, cesarean section, and forceps), bed turnover rate, occupancy rate, bed-days and operational beds, transfers to intensive care units (ICU), patient-days and discharges, breastfeeding within the first hours after birth, APGAR score, and Robson Classification.

The initiative prioritized structural process correction rather than temporary workarounds, resulting in complete and standardized systemic data collection. The availability of reliable indicators enabled analyses of appropriate delivery rates, volumetric planning of patients, beds, and obstetric staff, and monitoring of neonatal outcomes using internationally recognized metrics.

In particular, the implementation of APGAR score monitoring and Robson Classification, an internationally standardized tool for assessing, monitoring, and comparing cesarean section rates, strengthened clinical governance and benchmarking capabilities¹². The structured visibility of these indicators supported quality improvement initiatives and informed strategic decisions, including the adoption of advanced fetal monitoring technologies, such as Omniview-SisPorto, aimed at real-time assessment of fetal distress and reduction of adverse outcomes during childbirth¹³.

DISCUSSION

This study presents the stages that comprise the framework for data-driven solutions. The implementation of this framework contributes to fostering a data-oriented culture that generates tangible impacts on efficiency, information security, and the quality of hospital management. The distribution of requests over time, with sustained demand

across the study period, reflects the growing reliance on data-driven solutions to support clinical, operational, and strategic decision-making.

The three practical cases illustrate how the stages of the proposed framework translate into operational and clinical benefits across different healthcare contexts. Stage 1 (business understanding and project planning) was essential for aligning stakeholders and defining measurable objectives, as demonstrated in the Rehabilitation and Nutrition dashboards, where clinical and operational needs guided indicator selection. Stages 2 (data quality) and 4 (validation and delivery) consistently functioned as risk-control mechanisms by identifying inconsistencies between system records and local reference data, directly informing corrective actions and increasing trust in the analytical outputs delivered, particularly evident in the Nutrition and Childbirth cases. Stages 5 (monitoring and continuous improvement) and 6 (documentation) supported solution sustainability by enabling iterative refinement, reducing rework, and mitigating knowledge-loss risks associated with team turnover.

From an operational perspective, each case highlights a distinct dimension of the framework's value. Case 1 (Rehabilitation) emphasizes the consolidation of clinically meaningful indicators and longitudinal patient follow-up, supporting care planning and outcome monitoring. Case 2 (Nutrition) demonstrates gains in operational efficiency and financial impact through automation, workload reduction, and improved data completeness, directly supporting managerial and strategic decisions. Case 3 (Childbirth) underscores the role of data quality and clinical governance, where process redesign and mandatory data capture enabled the generation of standardized indicators to support benchmarking, quality improvement, and strategic technology adoption. Together, these cases reinforce that the framework's contribution extends beyond the volume of dashboards produced, encompassing reliability, usability, and decision-support capacity of the information delivered.

Beyond the case-specific examples, additional transversal actions further illustrate the framework's practical value. The identification of "test patients" in institutional databases, for example, relied on the combined application of data quality assessment, validation, and continuous improvement stages, enabling the exclusion of inconsistent records and preventing contamination of analytical results. Similarly, the identification and correction of errors in mechanical ventilator registration during the pandemic led to process standardization, ensuring consistency between clinical documentation and analytical datasets and supporting informed decisions regarding equipment acquisition.

Taken together, these findings demonstrate that the proposed framework consolidates institutional experience into a structured and sustainable approach to data management. By emphasizing validation, process understanding, and systematic identification of data inconsistencies, the framework supports not only the delivery of analytical solutions, but also long-term improvements in data governance, organizational learning, and decision-making practices.

LIMITATIONS

During the implementation of the solutions using the framework, the following limitations were identified:

Availability, standardization, and security of information: there are still restrictions regarding access, quality, and integrity of data, which affect the reliability of analyses.

System integration: the infrastructure and data integration span across different systems, such as electronic health records, online questionnaires, hospital management systems, and Excel spreadsheets, requiring additional time to develop the solutions.

Support and training: there is a lack of guides, tutorials, and training materials to assist staff from requesting departments in using the tools and accessing the data.

Technological resources: limitations in BI licensing hinder the development and distribution of the implemented solutions.

Context and institutional dependency: the framework was developed and applied within the context of the Brazilian supplementary health system and in a large private hospital with an established technological infrastructure and specialized data teams. These characteristics may limit the direct transferability of the proposed approach to organizations operating under different regulatory environments, resource availability, or levels of analytical maturity.

Absence of formal impact evaluation: although the framework supported the development of multiple dashboards within the department, this study did not include a formal quantitative evaluation of its impact on institutional outcomes, such as improvements in clinical results.

Potential institutional bias: the study was conducted by the same team responsible for developing and implementing the framework, which may introduce interpretation bias. Validation in other healthcare institutions would strengthen the proposed approach.

CONCLUSION

This study presented a practical framework for data management aimed at implementing business intelligence (BI) and data-driven healthcare solutions. The proposed approach outlined structured stages to facilitate the delivery of strategic solutions aligned with client needs, contributing to the identification of opportunities, process optimization, and improvement of healthcare quality.

The findings highlight the importance of integrating different technologies, adopting data governance practices, and investing in team capacity building to deliver reliable, scalable, and sustainable analytical solutions. As demonstrated across different operational contexts, the framework supports not only the production of analytical outputs, but also their effective use in clinical, managerial, and strategic decision-making.

By emphasizing validation, continuous improvement, and documentation, the framework contributes to strengthening data-oriented practices and organizational learning. Its application may support healthcare organizations seeking to enhance analytical maturity, improve information reliability, and sustain data-driven decision-making over time.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest related to this study.

AUTHORS' CONTRIBUTION

ADPH: conceptualization, methodology, validation, visualization, writing – original draft, and writing – review and editing. GMO: conceptualization, methodology, validation, visualization, writing – original draft, and writing – review and editing. LMK: conceptualization, data curation, formal analysis, methodology, validation, visualization, writing – original draft, and writing – review and editing. MGT: conceptualization and review. JMV: conceptualization and review. SBP: writing – review and editing.

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