Holistic Model of Advanced Analytics to Optimize Organizational Decision-Making

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***Abstract*—In increasingly data-intensive organizational environments, decision-making processes require analytical frameworks capable of integrating data governance, advanced analytics, and strategic interpretation under a unified structure. This study proposes a holistic advanced analytics model designed to optimize organizational decision-making through the integration of data quality, data integration, analytical capabilities, and data-driven storytelling within a continuous decision-support lifecycle. The proposed model was developed using the Design Science Research (DSR) methodology and structured according to the intelligence, design, and choice phases of the classical decision-making process. The framework incorporates internationally recognized standards and methodologies, including ISO/IEC 25012, ISO/IEC 11179, CRISP-DM, DataOps, and analytics value chain principles, enabling methodological interoperability and adaptive analytical governance. The resulting artifact was conceptually validated through expert judgment involving seven specialists in analytics, business intelligence, and organizational decision-making. The evaluation produced average scores ranging from 3.29 to 4.57 on a five-point Likert scale, with agreement levels reaching 85.71% in the highest-rated dimension. The results indicate favorable perceptions regarding the model's consistency, interpretability, usefulness, and organizational applicability. The proposed model contributes an integrative and adaptive framework that bridges fragmented analytical practices and supports more informed, scalable, and context-aware organizational decisions.**

Keywords—Advanced analytics; decision-making; holistic model; Design Science Research; expert judgment

I. Introduction

In an organizational environment characterized by complexity, uncertainty, and technological dynamism, data-driven decision-making has become a fundamental strategic pillar. However, recent research warns against the illusion that using data alone guarantees effective decisions, highlighting the need for more integrative and adaptive frameworks [1]. Given this reality, there is an opportunity to develop a holistic model of advanced analytics that considers not only data, but also by the four interrelated dimensions influencing decision quality.

Holistic thinking, characterized by the integration of multiple perspectives, has been shown to improve understanding and problem-solving in complex environments, especially when combined with traditional analytical approaches [2]. This approach has been validated in various contexts, from strategic leadership to inventory optimization using artificial intelligence [3]. Empirical evidence also supports the claim that organizations that adopt advanced analytics systems with a holistic orientation achieve significant improvements in organizational performance, innovation, and decision-making [4, 5].

Despite these advances, there remain significant gaps. Many organizations continue to evaluate decisions based on limited and linear criteria without adequately incorporating human-machine collaborative factors [6]. However, integrative models that articulate cultural, cognitive, technological, and social components under adaptive and multidimensional frameworks are lacking [7]. Recent studies emphasize that thinking style, digital orientation, organizational culture, and data connectivity are interdependent variables that, when treated in isolation, limit the impact of analytics on decision-making [8].

Therefore, this study aims to design and validate a holistic advanced analytics model capable of integrating data governance, analytical capabilities, visualization mechanisms, and organizational decision-support processes within a unified adaptive framework. This model is based on robust conceptual frameworks, such as systemic thinking, PDCA (plan, do, check, and act) cycle theory, bi-level optimization under uncertainty, and dual cognitive decision theories [9–11]. At the same time, it is recognized that the adoption of these models must consider the perception of value, resistance to change, and the challenges of practical implementation in different sectors [12].

In summary, this research aims to provide an integrative framework that overcomes the current limitations of fragmented analytics and strengthens organizations' ability to make smarter, more adaptive, and more sustainable decisions.

II. Related Work

A. Data Analysis and Decision-Making Models

Organizational decision-making models have evolved to address complexity and uncertainty in critical contexts. In [13], the authors proposed a model based on Fractional Continuous Fuzzy Sets (FCFS) that allows for a more flexible and sensitive representation of uncertainty using continuous functions instead of discrete values. This approach improves the accuracy of the evaluation of alternatives, such as the selection of industrial robots, where multiple technical criteria are considered. On the other hand, [14] analyzed the decision-making process in healthcare organizations during crises and identified three models: the CEO model (autocratic decision-making), the CEO-advisor model (participation of advisors), and the Top Management Team (TMT) model, which consists of a collaborative management team. These models reflect how leaders adapt their approach according to pressure and uncertainty and prioritize centralization or collaboration. In a similar context, [15] explored the emerging complexity in the decision-making process of chess players, demonstrating how the accuracy of decisions varies according to the competitiveness and critical nature of positions in the game. This study highlights the relevance of adaptive strategies in optimizing performance in competitive environments, such as minimizing decisiveness metrics. All three studies emphasize the importance of adapting decision models to the organizational context and the nature of the problem, whether technical or strategic.

The Analytics Value Chain model offers a maturity perspective on how organizations transform data into decisions, [16] classify analytical capabilities into four main approaches: descriptive, responds to what happened; predictive, anticipates what is likely to happen; prescriptive, suggests actions based on predictions; and autonomous, automates decisions using artificial intelligence, as shown in Fig. 1. The study [17] is a framework that aligns business analytics capabilities—descriptive, predictive, prescriptive, and autonomous—with Porter's value chain activities, illustrating how these capabilities enhance value creation at different stages of organizational processes. Their study highlighted the strategic application of analytics in primary (e.g., logistics and marketing) and supporting activities (e.g., HR and technology development), emphasizing measurable outcomes in value chain optimization. Building on this, [18] empirically validated the framework using case studies and secondary data, showing how firms leverage analytics for operational efficiency and competitive advantage, particularly in areas such as supply chain management and customer relationship analytics.

Fig. 1. Potential competitive advantage increases with more sophisticated analytics.

The Data-Driven Decision-Making (DDDM) paradigm emphasizes how the systematic use of data guides each phase of the decision-making process. In organizations that integrate large volumes of data through advanced analytics, DDDM improves the quality of decisions by relying on quantitative evidence rather than intuition or previous experience [19]. This has been demonstrated in areas such as marketing and strategic planning, where data enable the simulation of future scenarios and more informed decision-making [20].

B. Data Design, Analysis, and Management Methodologies

The Cross-Industry Standard Process for Data Mining (CRISP-DM) is a widely adopted methodology for structuring data mining projects, offering a systematic approach for extracting actionable insights from complex datasets. In [21], the authors applied CRISP-DM to predict student performance in e-learning environments, emphasizing its six-phase framework—business understanding, data understanding, data preparation, modeling, evaluation, and deployment—to identify at-risk students and reduce dropout rates. Their study highlighted the effectiveness of the random forest algorithm within this framework, achieving an 80% accuracy in predicting academic success. Similarly, [22] utilized CRISP-DM to automate complaint classification in e-commerce, demonstrating its flexibility in handling textual data through natural language processing (NLP) and machine learning. Their model achieved 85% accuracy, underscoring the utility of CRISP-DM for transforming raw data into structured solutions. Both studies illustrate the adaptability of CRISP-DM across domains, from education to customer service, while maintaining rigor in the data analysis and model evaluation (see Fig. 2).

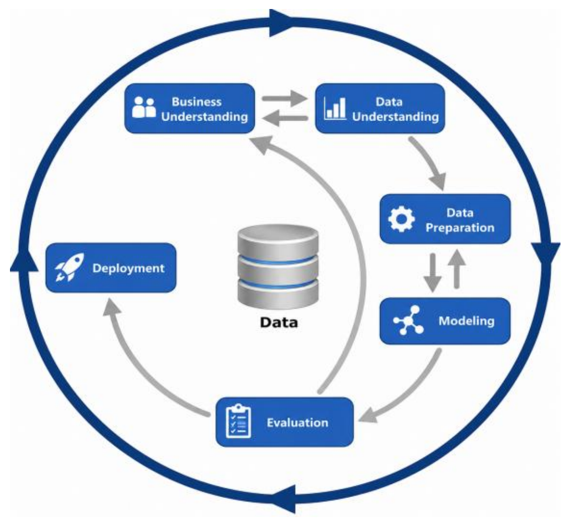

Fig. 2. CRISP-DM process diagram

Regarding the design of business intelligence solutions, Kimball and Inmon's approaches remain relevant as data warehouse modeling frameworks. Kimball proposed a bottom-up approach with an emphasis on dimensional modeling and ease of data access, which has been successfully applied in transactional flow solutions, such as the Data Mart designed for Peruvian bodegas, to analyze POS transactions and improve financial inclusion [23]. Similarly, [24] compares the approaches of Inmon, Kimball, and Data Vault, revealing that each method has an optimal scope of application depending on the project requirements. Inmon's approach is ideal when analytical requirements are not fully defined or when the stability of data sources is a priority, because its centralized 3NF structure ensures long-term consistency. On the other hand, Kimball's model excels in environments where query performance and end-user understanding are critical, especially in data-mart implementations with well-established requirements. In contrast, the Data Vault approach emerges as the most flexible solution for scenarios with multiple dynamic data sources or agile environments owing to its ability to scale without reengineering and maintain historical traceability. No approach is universally superior, and the choice should be based on factors such as data volatility, project timelines, and end-user needs. Kimball's methodology, shown in Fig. 3, continues to be widely used in various sectors of society. This approach, documented in his data warehouse lifecycle, covers all stages, from business planning to the delivery of analytical value [25].

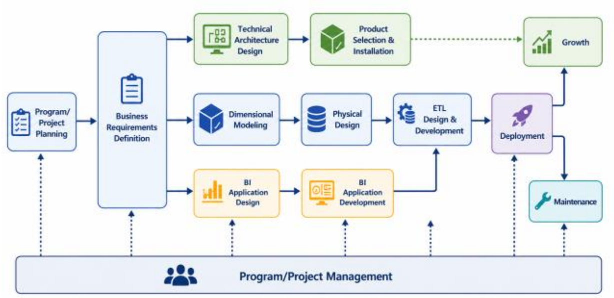

Fig. 3. Business dimensional life cycle diagram.

The Data Management Body of Knowledge (DAMA-DMBOK) framework has gained prominence in data governance due to its comprehensive approach to data quality, metadata management, and integration. A study by [26] proposed a new governance architecture called Horti-IoT, based on DAMA-DMBOK, applied to Dutch horticulture. The results showed significant improvements in the management and integration of data from sensors, images, and manual measurements, highlighting a reduction in analytical effort and an increase in the efficiency of agricultural monitoring.

The DataOps approach, which focuses on automating the data lifecycle and is inspired by Agile, DevOps, and lean manufacturing, has proven highly relevant in environments that require agility and continuous integration [27]. The authors demonstrated that applying this methodology in the feature selection and validation phases can reduce the complexity of datasets without compromising accuracy, achieving 82.32% accuracy with only four key variables. For their part, [28] developed a cloud-independent DataOps framework based on Kubernetes and Apache Iceberg, achieving a 12% reduction in query times through caching and improved scalability in Big Data applications. Their results demonstrated the impact of DataOps on data traceability, information quality, and decision-making efficiency. Together, the studies [27, 28] highlight the potential of DataOps to streamline workflows, shorten development cycles, and ensure robust data governance, thus establishing itself as a key component in modern data-driven organizations.

In complex organizational environments, the DSR methodology provides a rigorous methodological basis for the design and validation of scientific artifacts. This methodology not only emphasizes the creation of innovative solutions but also their systematic evaluation in real contexts. In [30], the authors stated that the DSR approach provides a systematic structure for the design, construction, and evaluation of improvement frameworks in construction processes, thereby ensuring scientific validity and practical relevance. In this study, the authors develop a framework that integrates Lean Construction, Building Information Modeling, and emerging technologies by using DSR to iterate between the design and empirical validation phases.

These methodologies and frameworks demonstrate how technical principles, combined with design and data governance strategies, strengthen organizational analytics models and enable the transition from storage to action with solid, controlled foundations.

C. *International Standards for Quality, Security, and Metadata*

The implementation of international standards in advanced analytics systems is essential for ensuring data quality, integrity, and security. The main standards related to this research are ISO/IEC 25012, ISO/IEC 11179, ISO/IEC 27001, and ISO 8000, where ISO stands for International Organization for Standardization and IEC for International Electrotechnical Commission, according to recent scientific literature.

The ISO/IEC 25012 standard provides a comprehensive framework for evaluating data quality based on a set of inherent characteristics and system-dependent completeness [31]. In the context of master data management, these characteristics are especially critical, as they ensure the reliability of core business entities that serve as authoritative references across organizational processes. The standard's multidimensional approach aligns with findings in specialized domains; for instance, in healthcare systems, data quality evaluation must consider not only syntactic accuracy, but also semantic precision and temporal relevance to support clinical decision-making. Similarly, industrial applications demonstrate that the ISO/IEC 25012 model effectively addresses measurement challenges through its structured property-based evaluation methodology, which enables organizations to systematically identify and prioritize data quality improvements [32].

With regard to metadata, ISO/IEC 11179 is recognized as the reference framework for metadata governance, particularly in the medical domain. In [33], the authors demonstrated its application in a pragmatic metadata repository that aggregated 466,569 unique medical metadata definitions, facilitating interoperability through standardized data elements. Similarly, [34] emphasized that repositories adhering to this standard enhance semantic interoperability by linking data elements to controlled vocabularies, which is critical for cross-institutional data integration. These studies underscore the role of the framework in ensuring semantic consistency and reliable information exchange in distributed environments.

Regarding security, the ISO/IEC 27001 standard has been widely adopted to protect information assets. According to [35], the framework derived from ISO/IEC 27001:2013 helps organizations identify, assess, and control risks while ensuring compliance with information security laws. Additionally, [36] emphasized its role in balancing privacy and utility in big data analytics, especially in the healthcare sector, strong data protection is essential.

Finally, the ISO 8000 standard plays a critical role in ensuring master data quality, particularly in sectors such as manufacturing and asset management, where consistency and traceability are crucial. As highlighted by [32], ISO 8000 provides a framework for evaluating and certifying master data repositories, emphasizing dimensions such as accuracy, completeness, and compliance—key factors in maintaining reliable "golden records" (p. 795). The study [37] further, ISO 8000's alignment with other standards (e.g., ISO 25012) enables organizations to address both inherent and system-dependent data quality challenges, reducing redundancies and improving interoperability (p. 4). By adhering to these principles, businesses can mitigate operational risks and enhance their decision-making processes. These regulations not only establish best practices but also provide an essential foundation for the design of advanced analytics models focused on data trust, interoperability, and sustainability.

D. Data Visualization for Decision-Making

Effective data visualization allows relevant information to be consolidated in an understandable manner, thus facilitating tactical and strategic decision-making in different organizational and social contexts.

Dashboards and Key Performance Indicators (KPI) have become essential tools for visualizing critical information in real time and facilitating informed decision-making. According to [38], the integration of dashboards into automated processes enabled the visualization of key indicators, such as response time and service level, which increased operational efficiency by 40% through Robotic Process Automation. For their part, [39] highlighted that the implementation of 22 standardized KPIs in dashboards allowed managers to comparatively analyze the performance of different organizational units and optimize strategic decisions. In both cases, real-time visualization not only improved efficiency and accuracy but also strengthened operational control and proactivity in organizational management.

Visual storytelling has established itself as a powerful tool for conveying complex information in an accessible and persuasive manner. In [40], the authors demonstrated the effectiveness of narrative techniques in mental health interventions, where they significantly improved life satisfaction among participants by facilitating emotional engagement and perspective shifts. Similarly, [41] highlighted the role of visual techniques, such as empty shots, in cinematic story-driven methods, showing how their distribution varies across genres to evoke specific emotional and dramatic effects. These studies underscore that effective storytelling combines meaningful visualization with a coherent narrative structure, enhancing understanding and engagement across diverse contexts from healthcare to film. By tailoring visual stories to audience needs—whether through therapeutic group discussions or genre-specific cinematic techniques—storytelling bridges gaps between data, emotion, and action, fostering deeper connections and informed decision-making.

Several studies in the field of Visual Analytics have demonstrated the potential to improve understanding and decision-making in various contexts. For example, [42] developed the Vulnerable Neighborhood Explorer (VNE) tool, which uses interactive visualization and clustering techniques to identify neighborhoods vulnerable to disasters, shows effective results in the analysis of socioeconomic disparities. On the other hand, [43] explored the use of generative AI agents to improve data visualization literacy and found that proactive agents with scaffolding techniques significantly increased student understanding. These studies collectively reveal that although numerous methodologies and frameworks—such as CRISP-DM, DataOps, Kimball, Inmon, and ISO standards—have advanced data management and analytical practices, most remain specialized for particular analytical stages or contexts.

Building upon this body of knowledge, the present study proposes a holistic advanced analytics model that unifies these methodologies under a single adaptive structure. Unlike traditional approaches that require changing frameworks depending on whether the analysis is descriptive, predictive, or prescriptive, the proposed model integrates them coherently, ensuring methodological continuity and adaptability across diverse organizational scenarios. This connection between the reviewed literature and the proposed model establishes a comprehensive foundation for data-driven decision-making in complex environments.

III. Methodology

This research is based on a combined methodological framework that integrates two complementary approaches: the Decision-Making Process Model and Design Science Research approach. This combination allows us to address the complexity of designing a holistic advanced analytics model to optimize organizational decision-making from both conceptual and empirical perspectives. Within this integrated design, the decision-making model supports the qualitative reasoning phase, while the DSR methodology incorporates quantitative evaluation metrics to ensure empirical validation.

A. Decision-Making Process Model

The classic decision-making process model [44] proposes three fundamental phases: intelligence, design, and choice. As illustrated in Fig. 4, this sequential, but iterative approach provides a structural framework for analyzing complex organizational decisions. Furthermore, [45] empirically examined the distribution of effort across the decision-making phases and found that managers devoted substantially more time to the design phase than to the intelligence and choice phases. This pattern remained consistent across different tasks and computing devices, providing empirical support for the applicability of Simon's model in describing how managers structure problem-solving activities in organizational contexts.

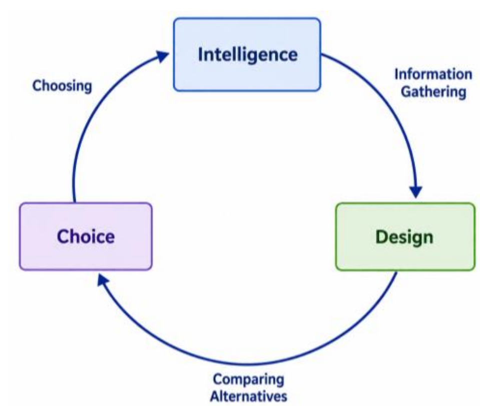

Fig. 4. Three-phase decision-making process model.

1) Intelligence defines this initial phase as the process of scrutinizing the environment to identify situations that require decisions. The author uses the term intelligence in its military sense, emphasizing the systematic collection of critical information that serves as the basis for action (p. 2).

2) Design explains that possible courses of action are generated and analyzed. Design involves creativity (invention of alternatives) and rigor (evaluation of feasibility), constituting a bridge between problem identification and the final selection (p. 2).

3) Choice described this phase as the selection of a specific alternative from among those available. He emphasized that the choice is not merely intuitive but must be based on the criteria established during the previous phases of intelligence and design (p. 2) [44].

B. Approach to Design Science Research (DSR)

The DSR approach provides an epistemological framework that guides the development of a model as a scientific artifact. According to [29] and [46], DSR follows an iterative structure that organizes the development of scientific artifacts through problem definition, objective formulation, artifact design, demonstration, evaluation, and communication, as illustrated in Fig. 5.

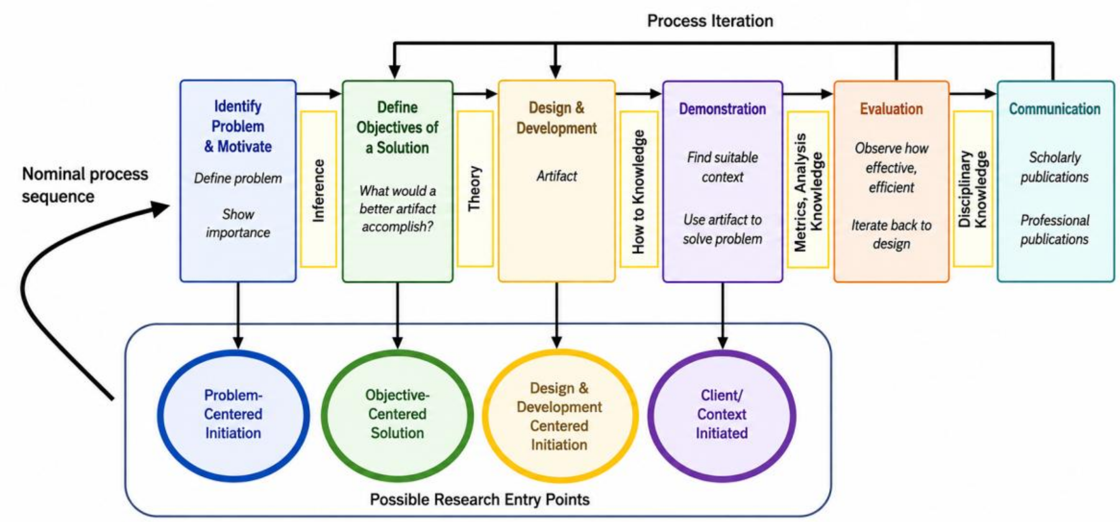

Fig. 5. DSRM process model

1) Identification of the problem and motivation [46] emphasizes that this phase requires clearly determining the research problem and justifying the worth of its solution. Conceptual decomposition of the problem allows its complexity to be grasped, while justification motivates both the researcher and audience. The author highlighted the need to understand the current state of the problem and the relevance of its solution (pp. 28-29).

2) Definition of objectives for the solution, according to [46], the objectives must be rationally derived from the identified problem, considering what is technically feasible. These can be quantitative (e.g., metric improvement) or qualitative (e.g., addressing unresolved problems). The author emphasized the importance of aligning these objectives with the requirements of the artifact, even when the solutions are partial or incremental (p. 29).

3) Design and development [46] describe this phase as the creation of artifacts—constructs, models, methods, or instantiations—that incorporate research contributions. He emphasized that the process requires defining both the functionality and architecture of the artifact, relying on existing theories to substantiate the solution (p. 29). This phase also involves validating the artifact through experimentation, simulations, case studies, or concrete tests which requires a thorough understanding of how to apply the artifact to solve the defined problem. (p. 30).

4) Evaluation [46] proposed comparing the observed results with the objective set using quantitative (e.g., performance) or qualitative metrics(e.g., user feedback). This phase may lead to iterations to refine the artifact or, if successful, to communicate the results (p. 30).

5) According to [46], this final stage consists of disseminating the problem, artifact, and its effectiveness to academic and professional audiences. Publications can be structured following the flow of the DSRM, such as how empirical studies follow a standard format (p. 30).

C. Evaluation Through Expert Judgment

The implementation of Expert Judgment as an evaluation phase in advanced analytics models is justified by its ability to validate the applicability and robustness of the proposed solutions in complex organizational contexts. As demonstrated by the study [47], in the validation of the ACDGE model for personalized learning pathways, Expert Judgment enables for the evaluation of content validity and internal consistency of a model through the participation of specialists with multidisciplinary experience (e.g., academics and professionals with over 30 years in the field). This approach not only ensures the relevance of the model's components (such as the implementation phase, where significant agreement was obtained with p=0.007) but also identifies areas for improvement, such as simplifying deliverables or incorporating teacher-student co-design.

However, [48] highlighted that expert judgment is key in scenarios with high technical uncertainty, such as the selection of technologies for the reuse of mining waste. Although their study revealed limitations in the distinguishability of alternatives when using questionnaires alone (distinguishability index <0.5), it highlighted that structured interviews with mineralogical design experts improved data quality by clarifying discrepancies and providing technical insights (e.g., chemical process optimization or market viability). This aligns with the need to evaluate advanced analytics models in organizational environments, where data heterogeneity and a lack of historical information require expert validation to reduce bias and ensure practical solutions.

To validate the proposed model, a questionnaire was developed based on instruments recognized in the scientific literature, which allows for the evaluation of key dimensions, such as usefulness, ease of use, understanding, and organizational applicability:

- Technology Acceptance Model (TAM): In [49], the authors state that TAM is widely used to predict the acceptance of technologies, with its core constructs being "perceived usefulness" and "ease of use", which are fundamental for understanding the intention to adopt technology.
- System Usability Scale (SUS): According to [50], SUS allows for quick and reliable measurement of a system's usability, considering elements such as comprehension and ease of interaction.
- Delphi method and expert judgment: In [51], the authors highlighted that the Delphi method allows for the structuring of a systematic process to reach consensus among experts and is highly effective in the evaluation of conceptual models and organizational decisions.

For the content validation of the holistic advanced analytics model, a panel of seven (7) experts was selected. This panel size is consistent with the recommendations of Lynn (1986) [52] and Escobar-Pérez and Cuervo-Martínez (2008) [53], who suggest that groups ranging from five to ten experts are methodologically adequate for content validation studies, ensuring sufficient representativeness and rigor in the assessment of complex constructs while avoiding unnecessary redundancy. The experts were selected through purposive sampling based on their academic qualifications, professional experience in analytics, business intelligence, organizational decision-making, and digital transformation. Each expert conducted the evaluation independently using a structured questionnaire, reducing the potential influence of group bias and strengthening the reliability of the validation process.

IV. Results

This section describes the phases proposed by the DSR methodology to rigorously structure the process of designing, constructing, and validating the proposed model. In particular, the artifact development is detailed through the six defined phases, encompassing everything from problem identification to model communication. Given that one of the key phases of DSR is evaluation, this methodological moment will be used to apply expert judgment as a validation mechanism by collecting specialists' perceptions of the quality and usefulness of the model. Finally, the alignment of each of the DSR phases with the stages of the decision-making process is presented, which reinforces the methodological consistency and practical applicability of the model in the real context of advanced analytics.

A. *Identification of the Problem and Motivation*

Various studies have shown that organizations face significant challenges in achieving effective decision-making due to fragmentation between data analysis models, the absence of integrated quality and security standards, and poor coordination between key performance indicators and analytical visualization strategies. These limitations result in poorly structured decision-making processes, with little technical support and low information traceability.

Based on this, it is evident that there is a need for an integrated solution that combines good data design and governance practices, advanced analytical tools, and visual resources to strengthen the decision-making process. This justifies the formulation of the following research question:

How can organizations optimize decision-making using a holistic model of advanced analytics?

B. *Define the Objectives of a Solution*

Based on the identified problem and the need to optimize organizational decision-making through a comprehensive approach to advanced analytics, the main objective of this work is to design and validate a holistic model that integrates the different levels of analytics (descriptive, predictive, prescriptive, and autonomous), as well as processes, standards, and data management methodologies, to strengthen DDDM.

This objective responds to various limitations detected in the literature, such as:

- Fragmentation between data analysis and management models,
- The absence of a methodological structure that integrates quality, security, and governance,
- Limited use of advanced visualization for interpreting critical data,
- And a lack of alignment between the analytical results and actual decision-making processes within organizations.

Therefore, the proposed solution addresses these gaps through the construction of a holistic analytical framework that unifies organizational context analysis, data quality governance, semantic integration, advanced analytical capabilities, and data-driven storytelling within a continuous decision-support lifecycle. The artifact was designed following DSR principles and conceptually validated through expert evaluation to ensure methodological consistency and organizational applicability.

C. Design and Development: Artifact

The design of the holistic advanced analytics model resulting from this research is shown in Fig. 6, which details the components, flows, and actions that comprise the developed artifact in a sequential and functional manner.

The Organizational Context, Table I, shows a sequence of key activities aimed at establishing strategic foundations, analytical requirements, and understanding of the organizational environment prior to working with data. These activities ensure that the advanced analytics process is aligned with business objectives, considering actual needs and available data sources.

The Data Cleaning and Quality, Table II, outlines the steps necessary to ensure that the data used is accurate, consistent, and useful. This stage is based on standards such as ISO 25012 and ISO 8000, which guide data quality management and employ techniques such as profiling and cleaning that are essential for reliable analytics.

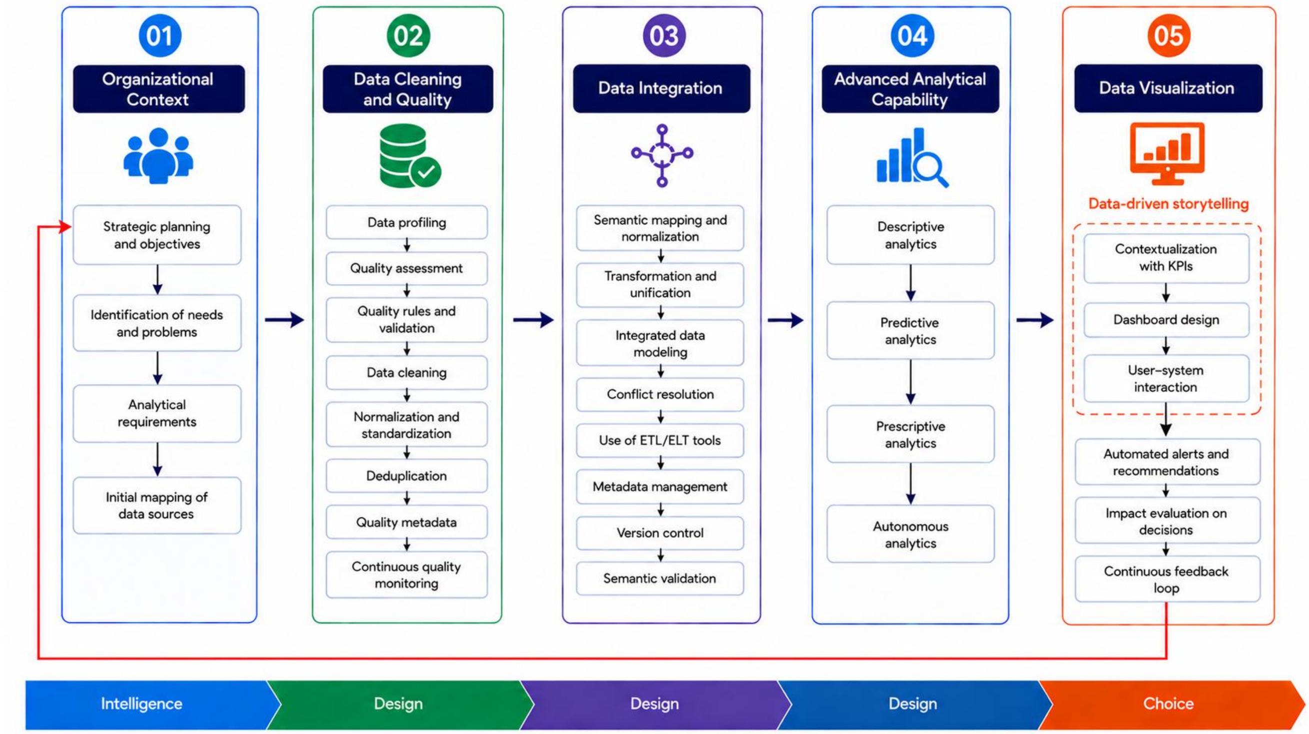

Fig. 6. Holistic advanced analytics model.

TABLE I. ORGANIZATIONAL CONTEXT

Activity	Purpose	Referenced Frameworks / Standards
Strategic planning and objectives	Define the strategic vision and goals for analytical implementation.	Data-Driven Decision-Making (DDDM)
Identification of needs and problems	Detect issues and opportunities for analytical intervention.	Process Model for Decision-Making
Analytical requirements	Establish analytical capabilities required to meet business needs.	DAMA-DMBOK
Initial mapping of data sources	Identify and list internal and external data sources.	DAMA-DMBOK, ISO/IEC 11179

TABLE II. DATA CLEANING AND QUALITY

Activity	Purpose	Referenced Frameworks / Standards
Data Profiling	Analyze data to understand its structure and quality.	DAMA-DMBOK, ISO 8000
Quality Assessment	Evaluate completeness, accuracy, and consistency of data.	ISO/IEC 25012, DAMA-DMBOK
Quality and Validation Rules	Define and apply data validation checks.	ISO/IEC 25012, Kimball
Data Cleaning	Correct errors, remove duplicates, handle missing values.	Crisp-DM, ISO 8000
Normalization and Standardization	Ensure data is in a consistent format.	ISO/IEC 11179, Kimball
Consolidation of Duplicates	Merge duplicate records for consistency.	DAMA-DMBOK
Quality Metadata	Document quality rules and attributes.	ISO/IEC 11179
Continuous Quality Monitoring	Ongoing tracking of data quality KPIs.	DataOps, ISO 8000

TABLE III. DATA INTEGRATION

Activity	Purpose	Referenced Frameworks / Standards
Semantic mapping and normalization	Align and translate terms across sources.	ISO/IEC 11179
Transformation and unification	Standardize formats and structures.	Kimball, Inmon
Integrated data modeling	Create a unified data representation.	Inmon, DAMA-DMBOK
Conflict resolution	Resolve data inconsistencies.	Kimball
Use of ETL tools	Extract, transform, and load data.	Kimball, DAMA-DMBOK
Metadata management	Organize metadata for integration and retrieval.	DAMA-DMBOK, ISO/IEC 11179
Version control	Track and manage changes to data.	DataOps
Semantic validation	Ensure integrated data meets defined semantics.	ISO/IEC 11179

The Data Integration, Table III, shows how the data from multiple sources are consolidated, transformed, and unified. This process is based on practices such as those of Kimball and Inmon for integration and modeling, and is supported by ETL (Extract, Transform, Load) tools and standards such as ISO/IEC 11179 for semantic and metadata management.

The Advanced Analytical Capability, Table IV, details the different advanced analytical capabilities aligned with the Data Analytics Value Chain. These capabilities enable the extraction of value from data using specific algorithms and models, according to the level of analytical maturity.

The Data Visualization, Table V, describes the activities necessary to transform the analytical results into understandable visual elements, aligned with the principles of visual analytics, storytelling, and data-driven decision-making. This phase reinforces organizational action through dashboards, KPIs, and continuous visual feedback.

TABLE IV. ADVANCED ANALYTICAL CAPABILITY

Activity	Purpose	Referenced Frameworks / Standards
Descriptive Analytics	Understand past behavior using statistical summaries.	Value Chain - Business Understanding; Algorithms: Histograms, Clustering
Predictive Analytics	Predict future outcomes using models.	Value Chain - Data Mining; Algorithms: Regression, Decision Trees
Prescriptive Analytics	Recommend actions based on predictions.	Value Chain - Deployment; Algorithms: Optimization, Simulation
Autonomous Analytics	Enable systems to decide and act independently.	Value Chain - Automation; Algorithms: Reinforcement Learning, Deep Learning

TABLE V. DATA VISUALIZATION

Activity	Purpose	Referenced Frameworks / Standards
Data-driven storytelling	Communicate insights through narratives.	Storytelling for Data, Visual Analysis
Contextualization with KPIs	Present insights aligned to performance goals.	DAMA-DMBOK
Dashboard design	Visualize key metrics clearly.	Visual Analytics, Kimball
User–system interaction	Enable users to explore and interact with data.	Visual Analysis, Human-Centered Design
Automatic alerts and recommendations	Provide proactive, rule-based guidance.	Prescriptive Analytics
Impact assessment on decisions	Evaluate analytical influence on outcomes.	Process Model Decision-Making

D. Demonstration

In order for the proposed artifact to demonstrate its applicability, we present an alignment between the phases of the holistic model of advanced analytics and the stages of the classic model of the decision-making process, which include three key moments: intelligence, design, and choice. This correspondence, as shown in Table VI, allows us to observe how the developed model offers structured support to each stage of the decision-making process.

In particular, the initial phase, called the Organizational Context, is designed to adapt to any type of organization, regardless of size, industry, or level of analytical maturity. Its purpose is to clearly establish needs, available data sources, and plans for future actions.

In addition, the model was evaluated by expert judgment, with the participation of seven professionals with experience in data analytics, visualization, and organizational decision-making. The results obtained in this evaluation, which are presented in the next phase, reflect positive acceptance in terms of the model's usefulness, applicability, and methodological alignment.

E. Evaluation (Validation)

A structured questionnaire was administered to a group of experts in advanced analytics and decision-making to evaluate the consistency, applicability, and usefulness of the developed holistic model.

Table VII shows the set of questions asked along with the criteria evaluated for each question.

TABLE VI. ALIGNMENT OF THE PHASES OF THE PROPOSED MODEL AND THE DECISION-MAKING MODEL

Holistic Model Phase	Functional Description	Decision-Making Phase
Organizational Context	Establishes strategic goals, identifies needs, defines analytical requirements, and maps data sources.	Intelligence
Data Cleaning and Quality	Ensures data reliability through profiling, validation, cleaning, standardization, and quality monitoring.	Design
Data Integration	Integrates and harmonizes data using ETL tools, metadata management, and semantic validation.	Design
Advanced Analytical Skills	Applies descriptive, predictive, prescriptive, and autonomous analytics to explore alternatives.	Design
Data Visualization	Presents analytical insights through storytelling, KPIs, dashboards, and user interaction for decision support.	Choice

TABLE VII. QUESTIONS FROM THE VALIDATION INSTRUMENT AND CRITERIA EVALUATED

Nº	Question	Criterion evaluated
1	The proposed model adequately reflects the key phases of a data-driven decision-making process.	Functional relevance
2	The phases of the model are clearly defined and understandable for implementation in an organization.	Structural clarity
3	The model adapts to different organizational contexts without the need for structural changes.	Organizational flexibility
4	The model appropriately integrates recognized frameworks and methodologies (e.g., ISO 25012, DSR, TD Process Model).	Methodological alignment
5	The relationships between the phases of the model are consistent and logically sequential.	Logical consistency
6	The model can be replicated by other researchers or professionals with minimal ambiguity.	Reproducibility
7	The analytical capabilities described (descriptive, predictive, prescriptive, autonomous) are correctly classified.	Functional classification
8	The inclusion of the visualization phase (KPIs, storytelling, dashboards) contributes to the understanding and use of the results.	Interpretative capacity
9	The model adds value to organizational decision-making from a holistic and integrative approach.	Organizational added value
10	I believe that the proposed model is useful and applicable for improving decision-making processes based on advanced analytics.	General assessment of usefulness

Table VIII shows the results of seven experts in the fields of data analysis, visualization, and business intelligence who answered the questionnaire. Each question was rated on a Likert scale from 1 to 5, where 1 represents “strongly disagree”, and 5 represents “strongly agree”. Three indicators were calculated for each question: average, standard deviation, and percentage of responses equal to or greater than four.

TABLE VIII. RESULTS OF MODEL VALIDATION ACCORDING TO EXPERT JUDGMENT.

Question	Average	Standard deviation	Percentage ≥ 4
Q1	3.71	1.03	57.14%
Q2	4.14	1.12	71.43%
Q3	3.57	0.49	57.14%
Q4	3.71	0.70	57.14%
Q5	3.57	1.18	57.14%
Q6	3.71	0.88	71.43%
Q7	3.71	0.88	71.43%
Q8	4.57	0.73	85.71%
Q9	3.29	1.03	42.86%
Q10	3.71	1.03	57.14%

1) Average: The average score for each question indicated the overall degree of acceptance of each dimension evaluated in the model. Most of the averages were between 3.5 and 4.5, which are positive and shows a favorable trend toward the usefulness and applicability of the proposed holistic model.

2) Standard deviation: This value measures the variability of the responses. Lower values indicate consensus among the experts. For example, question Q3 had a low deviation (0.49), suggesting that experts closely agreed with their responses. Conversely, a deviation of 1.18 (Q5) indicated greater dispersion and possibly divergent views on that dimension.

3) Percentage ≥ 4: This indicator represents the degree of acceptance (high ratings). It can be seen that:

a) Q8: Visualization and interpretation of results had the highest level of acceptance (85.71%), reflecting a high positive consensus.

b) Q9: Obtained the lowest agreement percentage (42.86%), which provided valuable feedback for refining the organizational adaptability dimension of the proposed model. This result contributed to the iterative improvement of the artifact by identifying the need to strengthen contextual flexibility and clarify the integration mechanisms across heterogeneous organizational environments. From a DSR perspective, this feedback was considered a constructive input for the evolution and maturation of the proposed framework.

F. Communication

The Communication phase of the DSR methodology is evidenced through the presentation and dissemination of the results of the developed holistic model, as part of a doctoral research study. The results of the questionnaire administered to seven experts indicate that the proposed model is conceptually coherent, methodologically sound, and relevant to the stated objectives. Most of the indicators per question are above the recommended acceptance thresholds, with averages higher than 3.5 and agreement levels (ratings of 4 or 5) exceeding 60% in most of the evaluated dimensions.

These findings support the validity and applicability of the model in real contexts, constituting a contribution expected to benefit the academic and professional community interested in data-driven decision-making processes based on advanced analytics. The publication of this scientific study serves as a formal dissemination mechanism, thereby fulfilling the principles of the Communication phase of the DSR methodology.

V. Discussion

A comparison of the proposed holistic model with the reviewed literature clearly shows that existing contributions address only partial dimensions of the analytical process and fail to provide an integrative structure that articulates data quality, methodologies, governance, analytical capabilities, and effective decision support. The holistic character of the proposed model lies in its cyclical and adaptive structure, which integrates the analytical process from descriptive capabilities to autonomous decision-support mechanisms, while maintaining continuous feedback for organizational improvement [16–18], [27–29]. Validation with experts supports this reading, reflecting recognized strengths in visualization, structural clarity, and reproducibility of the model, as well as areas where challenges remain, particularly in organizational adaptability

Firstly, models based on uncertainty representation, such as the FCFS approach [13], provide an important advance for evaluating alternatives in highly technical contexts. However, their application is restricted to the methodological level of calculation, without incorporating data lifecycle management mechanisms, quality standards, or strategic elements that enable their use within complex organizational processes. The proposed model extends these approaches by structuring an adaptive analytical lifecycle that integrates governance standards, semantic interoperability, data quality management, analytical scalability, and decision-oriented visualization mechanisms under a unified framework.

On the other hand, crisis decision-making models proposed in the healthcare context, such as the CEO, CEO–advisor, and TMT approaches [14], emphasize leadership styles and governance in high-pressure environments. While they provide relevant insights into decision-making dynamics, these models do not consider the data engineering processes or analytical support necessary for evidence-based decisions. In contrast, the holistic model articulates the classic decision-making process with data analysis methodologies, governance standards (ISO 25012, ISO/IEC 11179, ISO 8000, ISO/IEC 27001), and visualization mechanisms geared toward decision-making.

Similarly, evidence of emerging complexity in human decisions, such as that observed in the analysis of chess players' behavior [15], demonstrates the importance of adaptability and situational reasoning. Nevertheless, these studies are limited to specific domains and do not constitute frameworks applicable to the organization of an advanced analytics process. The present model integrates the principle of adaptability through continuous feedback, scaled analytical capabilities, and permanent monitoring mechanisms, expanding its application to multiple sectors.

Likewise, frameworks such as the Analytics Value Chain [16] and proposals linking analytical capabilities to the organizational value chain [17, 18] have made it possible to conceptualize the progression from descriptive analysis to autonomous analytics. However, these approaches focus on the functional classification of capabilities, without offering a methodological roadmap that articulates standards, data quality, semantic integration, or evaluation mechanisms. The proposed model extends these contributions by structuring operational phases that include cleaning, integration, modeling, and visualization, along with formal quality assurance mechanisms based on ISO 25012 and ISO 8000.

In terms of methodology, CRISP-DM [21, 22] continues to be a widely used standard, especially in data mining projects. Its main limitation lies in its technical approach and its lack of integration with governance models, international standards, or organizational decision-making processes. For its part, DataOps [27, 28] introduces automation, version control, and continuous orchestration, but focuses on pipeline engineering rather than decision support. The holistic model combines both approaches under a higher framework based on DSR, which allows for the integration of design, validation, communication, and continuous improvement.

Finally, the expert validation results reinforce the conceptual coherence of the model. The high acceptance rate of the visualization phase (85.71% of responses ≥4) confirms the importance of translating analytical results into actionable knowledge. In contrast, the lower agreement levels obtained for functional relevance (Q1, 57.14%) and holistic organizational value (Q9, 42.86%) provided valuable input for refining the proposal. Regarding Q1, expert feedback revealed the need to make the relationship between the analytical process and organizational decision-making more explicit. Consequently, the model was refined by incorporating a transversal representation of decision-making throughout the analytical lifecycle, strengthening the connection between analytical capabilities and organizational outcomes. Similarly, the results obtained for Q9 highlighted the importance of reinforcing the continuous improvement perspective. As a result, a cyclical feedback mechanism was incorporated, connecting the data visualization stage with the organizational context and enabling iterative refinement across the analytical lifecycle. These refinements strengthen the model's holistic character by integrating not only the complete advanced analytics cycle but also continuous organizational learning, adaptation, and decision support.

VI. Conclusion

This study proposed and validated a holistic advanced analytics model aimed at optimizing organizational decision-making through the integration of data governance, semantic integration, analytical capabilities, visualization mechanisms, and data-driven storytelling. Unlike fragmented analytical approaches, the proposed framework structures the analytical process as a continuous and adaptive decision-support lifecycle aligned with the intelligence, design, and choice phases of classical decision-making theory.

The application of DSR enabled the iterative development and conceptual validation of the proposed artifact. Expert evaluations indicated favorable perceptions regarding the model's structural coherence, interpretability, and organizational applicability, particularly in the visualization and analytical integration phases.

The proposed framework provides to the current body of knowledge by providing an integrative structure capable of connecting data quality standards, integration methodologies, advanced analytics, and decision-support visualization within a unified organizational context. Furthermore, the incorporation of continuous feedback mechanisms strengthens the adaptive capacity of the model in dynamic and data-intensive environments.

VII. Future Works

Future research will focus on implementing and testing the proposed holistic advanced analytics model in real organizational environments to evaluate its practical effectiveness, scalability, and adaptability across different sectors. Such empirical validation will provide additional evidence regarding the model's contribution to organizational decision-making and its applicability in diverse operational contexts.

The next stage of this ongoing research involves developing a computational tool that integrates all phases of the proposed model, facilitating its operational deployment, automation, and scalability. Comparative studies with existing analytical and decision-support frameworks will also be conducted to assess the relative advantages, limitations, and organizational impact of the proposed model, as well as to identify best implementation practices.

Additionally, the incorporation of emerging technologies—such as generative artificial intelligence, the Internet of Things (IoT), and blockchain—is proposed to expand the model's analytical, governance, and automation capabilities. Future studies will also explore the integration of cognitive analytics capabilities to enhance contextual reasoning, knowledge discovery, interpretation of unstructured information, and human-centered decision support in complex organizational environments.

Furthermore, the model will be adapted and tested within specific sectors, including healthcare, education, and logistics, to validate its contextual flexibility and sector-specific applicability. Finally, future work will focus on the computational operationalization of the proposed framework through the development of an interoperable analytical platform capable of automating the model lifecycle in real organizational environments and enabling longitudinal evaluations of its impact on analytical maturity, data governance, digital transformation, and organizational performance.

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