Empirical Validation and Enhancement of ADiBA: A Framework for Big Data Analytics Implementation

Norhayati Daut[1], Naomie Salim[2], Sharin Hazlin Huspi[3], Anazida Zainal[4], Chan Weng Howe[5], Muhammad Aliif Ahmad[6], Siti Zaiton Mohd Hashim[7], Masitah Ghazali[8], Mohd Adham Isa[9], Rashidah Kadir[10], Nuremira Ibrahim[11], Norazlina Khamis[12]

Faculty of Computing and Informatics, Universiti Malaysia Sabah, Sabah, Malaysia[1, 12]
UTM Big Data Centre, Universiti Teknologi Malaysia, Johor, Malaysia[1, 2, 9]
Faculty of Computing, Universiti Teknologi Malaysia, Johor, Malaysia[3, 4, 5, 6, 7, 8, 10]
Faculty of Built Environment and Surveying, Universiti Teknologi Malaysia, Johor, Malaysia[11]

***Abstract*—The implementation of Big Data Analytics (BDA) in organisations requires a structured approach to ensure alignment with strategic goals and infrastructure readiness. This study presents an enhanced version of the previously published ADiBA (Accelerating Digital Transformation Through Big Data Adoption) framework that aimed at guiding organizations through critical components necessary for successful BDA implementation. The initial framework was developed based on systematic literature review. To validate and refine the framework, a mixed-methods survey was conducted among domain experts using a five-point Likert scale and open-ended questions to assess the relevance of each framework component. Quantitative responses were analysed using the Content Validity Index (CVI), with a threshold of 0.78 adopted as the minimum acceptable I-CVI score for each item. Complementing the quantitative analysis, qualitative feedback from the open-ended survey responses, Focus Group Discussions (FGDs), and in-depth interviews were examined through thematic analysis, revealing key themes related to framework's clarity and operational aspects. Insights from both analyses informed the refinement of several components. The resulting framework is a validated and empirically-informed guide designed to support effective BDA implementation in organizational contexts.**

Keywords*—Adoption process; big data; big data analytics; framework; framework validation; expert survey; content validity index; thematic analysis; organizational implementation; digital transformation

I. INTRODUCTION

The implementation of BDA within organizations has emerged as an important factor in driving digital transformation and informed decision-making. Despite its significance, many organizations encounter challenges in effectively integrating BDA into their operations, often due to the absence of structured implementation frameworks. These challenges include data quality and integration, infrastructure and scalability issues, and shortage of skilled professionals [1].

While several BDA implementation frameworks has been proposed, a significant number lack empirical validation, limiting their practical applicability. This gap underscores the need for frameworks that are not only theoretically sound but also validated through expert insights to ensure relevance and effectiveness in real-world settings. In response to this, this paper aims to validate and refine a previously developed framework named ADiBA [2], designed to adopt and implement BDA in organizations. Although the initial construction of the framework was based on literature and theoretical model, validation is highly advisable to ascertain its relevance to practical settings.

To facilitate this, expert feedback obtained through structured surveys and FGDs. The quantitative data from the survey were analysed using CVI to assess the relevance of each framework component, while qualitative insights from open-ended responses and FGDs were examined through thematic analysis. The analyses were then used to determine which aspects require changes to achieve the intended objectives.

The primary objective of this study is to enhance the proposed ADiBA framework's validity and practical utility by integrating expert insights, thereby contributing a more robust tool for organizations navigating BDA implementation. By addressing the existing gap in empirically validated frameworks, this research offers a refined, expert-informed model that can serve as a valuable resource for practitioners and research alike.

To achieve these objectives and present our findings comprehensively, the remainder of this paper is structured as follows: Section II provides the background of the previously developed ADiBA framework, including the theoretical models that guided its initial construction. Section III details the mixed method methodology employed for framework validation, covering participant selection and data analysis techniques. Section IV presents the quantitative and qualitative results derived from the expert feedback. Section V outlines the enhancements made to the ADiBA framework based on these findings. Finally, Section VI concludes the paper by summarizing key contributions and discussing avenues for future research.

II. BACKGROUND

The implementation of BDA within organizations has emerged as an important factor in driving digital transformation and informed decision-making. Despite its significance, many organizations encounter challenges in effectively integrating BDA into their operations, often due to the absence of structured implementation frameworks.

Numerous studies highlight the critical need for proper frameworks, models, or methodologies to successfully implement BDA. For instance, optimizing BDA process is challenging, as it involves combining diverse data assets to produce actionable insights [3]. and improved decision making [4], [5]. Similarly, a business-driven reference architecture is a viable solution to address the high failure rate of BDA implementation projects in public sector organizations, emphasizing the need to systematically consider business use cases and processes before assembling technical aspects [6]. As highlighted in [7], many BDA projects fail or do not deliver promised business value, often due to technical issues (data consolidation, quality, visualization), managerial challenges (inability to gain insights and link them to business problems), and organizational obstacles (changes in decision-making, culture, and clear direction of initiatives). The lack of a structured approach not only can jeopardize decision-making, but also prevent organizations from capitalizing on market opportunities, ultimately compromising their capacity to create value [8]. Furthermore, a significant gap between existing frameworks and the integration of big data into various business functions, explicitly stating the need for developing new models and implementation frameworks for better insights and patterns [9].

While the emerging interest in BDA has led to the proposal of various BDA implementation frameworks, a significant gap persists in the exiting literature. Many of these proposed frameworks primarily focus on the technical aspects of BDA implementation, often overlooking crucial dimensions such as people, organizational structure, culture, and strategic alignment. This narrow focus limits their holistic applicability and can lead to incomplete or unsustainable BDA initiatives within complex organizational environments. Furthermore, a substantial number of these studies propose frameworks without subjecting them to rigorous validation or verification processes, raising questions about their practical utility and real-world effectiveness.

In response to this gap, the ADiBA framework was developed to provide a structured approach to BDA implementation. This framework was initially formulated through a systematic literature review (SLR), which identified key components, steps, and activities essential for successful BDA implementation. The components of ADiBA framework (Fig. 1) are:

1) *Prepare immersion of analytic culture:* Ensure that organizations can fully leverage data-driven insights for decision-making and strategic growth.

2) *Business understanding:* Define clear objectives, identifying challenges, and ensuring that analytical efforts contribute to business value

3) *Data management and governance:* Ensure that data is accurate, secure, compliant, and valuable for decision-making

4) *Project planning:* Define project objectives, allocate resources effectively, and assess the potential risks and benefits.

5) *Data understanding:* Ensure that the data used is relevant, accurate, and suitable for analysis and modelling.

6) *Data preparation:* Transform the data into usable format for analysis and modelling.

7) *Tool, infrastructure and technology procurement and presentation:* Acquire and deploy necessary technological resources.

8) *Business analytics modelling:* Create analytical models that interpret data to provide actionable insights.

9) *Data analytics product development:* Transform insights derived from analytics into dashboards, and reports.

10) *Evaluation of model and products:* Assessing the performance of analytics modelling and visualization.

11) *Data analysis product deployment:* Transition the product from development phase to live production environment.

12) *Monitoring, maintenance and upgrades:* Monitor the performance, perform regular maintenance, and implement upgrades.

13) *Inculturation of big data analytics into business:* Foster data-driven decision-making, improves operational efficiency, drives innovation, supports strategic planning, and encourages continuous improvement.

The theoretical grounding of ADiBA framework draws upon established model such as the Cross-Industry Standard Process for Data Mining (CRISP-DM) model [10], Kotter's 8-step model [11], DAMA-DMBOK Data Management [12], Data lifecycle [13], and Project Management lifecycle [14]. These models were specifically selected and integrated based on their demonstrated utility in various studies that proposed frameworks for BDA implementation, technology adoption, and organizational change, ensuring a robust foundation for ADiBA.

The CRISP-DM model is a widely adopted, structured methodology for managing data mining projects. It encompasses six iterative phases to provide a comprehensive framework that ensures a systematic approach to data analytics. The Kotter's 8-step model is designed to assist leaders in effectively managing organizational transformation by identifying potential sources of resistance and developing strategies to address them, thereby facilitating a smoother change process. The DAMA-DMBOK framework outlines best practices across key data management areas such as data governance and quality, ensuring robust data management practices. The Data lifecycle models describe the progression of data from creation to disposal, ensuring effective data management throughout its lifespan. Finally, the project management lifecycle offers a structured framework that guides projects from initiation to completion, enhancing the likelihood of success.

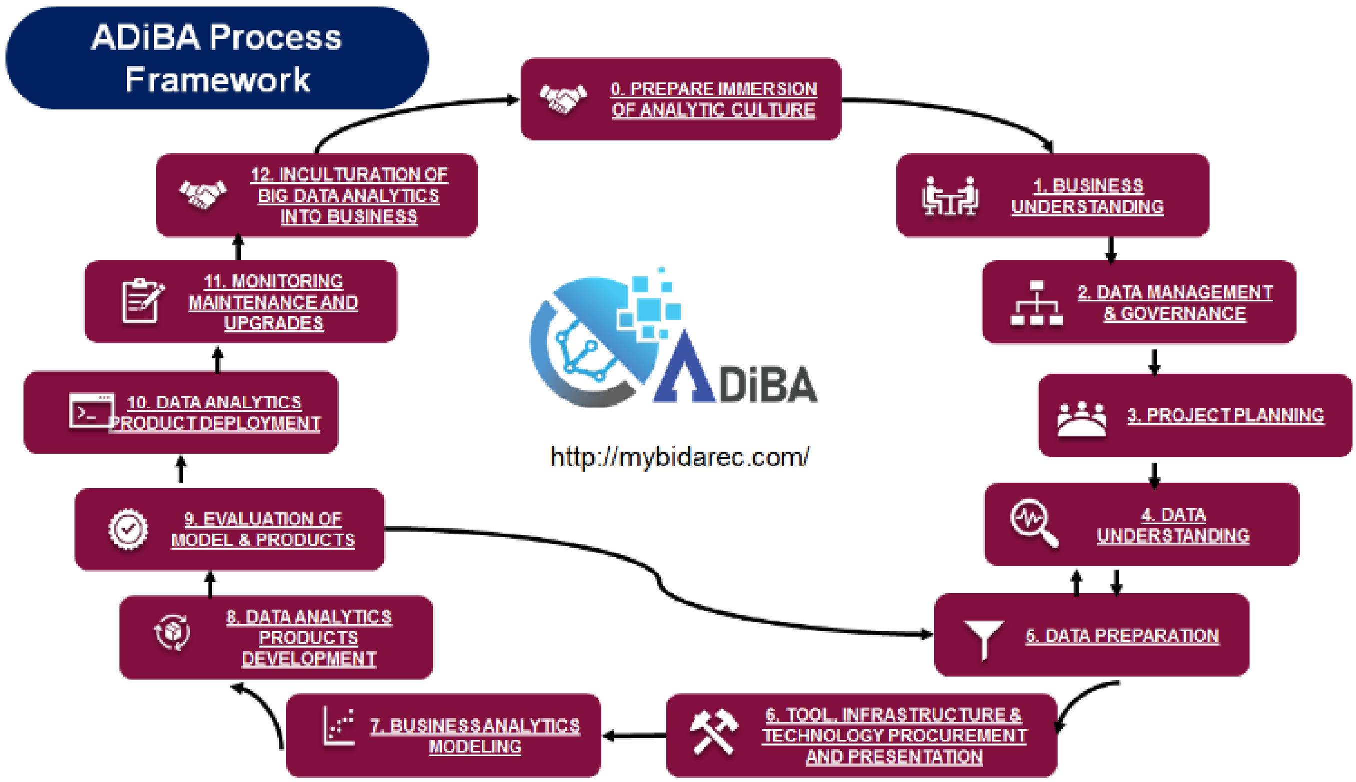

Fig. 1. ADiBA framework.

By synthesizing these models, the ADiBA framework offers a holistic approach to BDA implementation, deliberately addressing both technical execution and the crucial non-technical dimensions of strategic alignment, data management, and organizational change. The ADiBA framework has a step-by-step approach with tools and guidelines that can be used by organizations to implement BDA. These steps can be tailored and adopted selectively based on size, types, resources, and analytics goals of organizations.

Building upon the theoretical foundations and the structured components of the ADiBA framework, this study seeks to validate and refine the framework to ensure its practical applicability in organizational settings. To achieve this, a comprehensive methodological approach was employed, combining quantitative assessments with qualitative insights. The following section details the research design, data collection methods, and procedures to evaluate the relevance of the ADiBA framework in facilitating BDA implementation

III. Methodology

This study adopted a mixed-methods research design to validate and refine the ADiBA framework. The section details the development of the evaluation instrument, the selection criteria for domain experts, the procedures for data collection, and the quantitative (CVI) and qualitative (thematic analysis) approaches used for data analysis. The following subsections elaborate on each methodological phase.

A. Development of Evaluation Instrument

The survey was crafted to assess the relevance of each component within the ADiBA framework. It comprises both quantitative and qualitative elements to capture a holistic view of expert opinion.

For the quantitative assessment, a series of 4-point Likert scale questions were developed for each task (item) under the framework's component that ranged from 1 to 4, where 1 represents “not relevant”, 2 represents “somewhat relevant”, 3 represents “relevant”, and 4 represents "highly relevant". Experts can rate the degree to which each task is applicable and essential within their organizational context. The objectives of assessing the tasks of each component are summarized in Table I.

Complementing the quantitative data, the survey incorporated open-ended questions aimed at eliciting qualitative insights. For each component, experts were invited to suggest any revisions or provide comments on the respective tasks and components. Additionally, a concluding open-ended question sought their overarching thoughts and recommendations concerning the entire ADiBA framework. The questions addressed topics such as the necessity of a structured methodology to implement BDA in organizations and the potential challenges organizations might encounter. These qualitative responses were subjected to thematic analysis, enabling the identification of common themes and nuanced perspectives that could inform further refinement of the framework.

TABLE I. OBJECTIVES FOR TASKS OF ADIBA FRAMEWORK COMPONENTS

Framework Component	Task	Objective
PREPARE IMMERSION OF ANALYTICS CULTURE	0.1	To assess the relevance of creating urgency among members of organization
	0.2	To assess the relevance of building a guiding coalition among members of organization
	0.3	To assess the relevance of creating a vision for change among members of organization
	0.4	To assess the relevance of communication the vision among members of organization
	0.5	To assess the relevance of removing barriers that can hinder the change among members of organization
	0.6	To assess the relevance of creating short-term wins for the organization
	0.7	To assess the relevance of building on the change among members of organization
	0.8	To assess the relevance of anchoring the change in the organizational culture
BUSINESS UNDERSTANDING	1.1	To assess the relevance of identifying the organization’s business goal
	1.2	To assess the relevance of assessing the organization’s current situation
	1.3	To assess the relevance of defining the organization’s data analytics goals or insights
DATA MANAGEMENT & GOVERNANCE	2.1	To assess the relevance of defining the data governance engagement framework
	2.2	To assess the relevance of defining the data governance organization
	2.3	To assess the relevance of developing data security, privacy, sharing, ethics and compliance governance framework
PROJECT PLANNING	3.1	To assess the relevance of identifying organization’s business use cases
	3.2	To assess the relevance of estimating the resources required for data analytics project
	3.3	To assess the relevance of performing cost-benefit analysis before starting any data analytics project
	3.4	To assess the relevance of developing a project plan for data analytics project
DATA UNDERSTANDING	4.1	To assess the relevance of defining sources of the data required
	4.2	To assess the relevance of designing and developing data sandbox
	4.3	To assess the relevance of describing the data required
	4.4	To assess the relevance of developing engines for data curation
	4.5	To assess the relevance of verifying the quality of data
DATA PREPARATION	5.1	To assess the relevance of extracting the data required
	5.2	To assess the relevance of transforming the extracted data
	5.3	To assess the relevance of exploring and visualizing the data
	5.4	To assess the relevance of modifying the data
TOOL, TECHNOLOGY, AND INFRASTRUCTURE PROCUREMENT & PRESENTATION	6.1	To assess the relevance of identifying the required tool, technology and infrastructure
	6.2	To assess the relevance of evaluating the required tool, technology and infrastructure
	6.3	To assess the relevance of procuring the required tool, technology and infrastructure
BUSINESS ANALYTICS MODELING	7.1	To assess the relevance of identifying key variables for data analytics modelling
	7.2	To assess the relevance of selecting the suitable modelling techniques
	7.3	To assess the relevance of designing the testing and training dataset
	7.4	To assess the relevance of building the data analytics model
	7.5	To assess the relevance of assessing the data analytics model
	7.6	To assess the relevance of managing the data analytics model
	7.7	To assess the relevance of deploying the data analytics model
DATA ANALYTICS PRODUCT DEVELOPMENT	8.1	To assess the relevance of pre-designing the data analytics product
	8.2	To assess the relevance of designing and developing dashboards
	8.3	To assess the relevance of designing and developing business reports
	8.4	To assess the relevance of developing alerts
EVALUATION OF MODEL AND PRODUCT	9.1	To assess the relevance of performing the data analytics product testing
	9.2	To assess the relevance of performing pilot test

Framework Component	Task	Objective
EVALUATION OF MODEL AND PRODUCT	9.3	To assess the relevance of preparing test report
	9.4	To assess the relevance of determining the next course of actions
DATA ANALYTICS PRODUCT DEPLOYMENT	10.1	To assess the relevance of planning the data analytics product deployment
	10.2	To assess the relevance of planning the monitoring and maintaining the data analytics product
	10.3	To assess the relevance of reporting the final results
	10.4	To assess the relevance of reviewing the data analytics project
MONITORING, MAINTENANCE AND UPGRADES	11.1	To assess the relevance of monitoring the performance of data analytics product
	11.2	To assess the relevance of correcting any errors occurred
	11.3	To assess the relevance of enhancing dashboards, reports, and alerts if required
	11.4	To assess the relevance of replacing or discarding the data analytics product if obsolete
INCULTURATION OF BIG DATA ANALYTICS INTO BUSINESS	12.1	To assess the relevance of generating short-term wins
	12.2	To assess the relevance of sustaining the change in the organization culture
	12.3	To assess the relevance of anchoring the change in the organization culture
	12.4	To assess the relevance of assessing the impact of big data analytics on organization

B. Selections of Experts

To ensure a comprehensive evaluation of the ADiBA framework, domain experts with substantial experience in BDA implementation were selected. These experts were identified through professional networks, industry conferences, and academic collaborations. Invitations outlining the study's objectives and the importance of their participation were sent via email. Table II shows the number of selected experts and their organization.

Even though many experts do not have a formalized framework or methodology for implementing BDA in their organizations, their hands-on experience enables them to determine which components are appropriate and effective when developing and executing BDA projects. This practical knowledge ensures that their evaluations are grounded in real-world applicability, contributing to their organization's progression toward becoming data-driven.

TABLE II. LIST OF EXPERTS

Organization	No of Experts	Government/non-government	Domain
Jabatan Digital Negara	3	Government	ICT
Malaysia Digital Economy Corporation (MDEC)	2	Government	ICT
Malaysia International Shipping Corporation Berhad (MISC)	1	Government	Shipping
Ebdesk Malaysia Sdn. Bhd	1	Non-Government	ICT
Malaysia Marine and Heavy Engineering Holdings Berhad (MMHE)	2	Government	Oil and Gas, Construction
Johor Land Berhad (JLAND)	1	Government	Real Estate
REFREX Sdn. Bhd.	1	Non-Government	ICT
Rebaie Analytics Group	1	Non-Government	ICT
Big Data Institute	1	Non-Government	ICT

C. Data Collection

Data were collected through a structured approach during FGDs sessions, integrating both quantitative and qualitative methods. Two FGDs were conducted as part of the study. The first session took place in Selangor, Malaysia and include representatives from Jabatan Digital Negara, MDEC, MISC, and Ebdesk Malaysia. The second FGD was held in Johor, Malaysia with participation from MHHE, JLAND, and REFREX. Each FGD session commenced with the administration of the framework evaluation survey. This was followed by a facilitated discussion encouraging participants to share their perspectives, allowing them to provide qualitative feedback, suggest revisions, and discuss the applicability of the framework's component in real-world organizational setting.

For the surveys, responses were recorded directly into a digital format, ensuring ease of analysis. The data were then utilized to calculate the CVI. For the qualitative components, a systematic note-taking and reconciliation process was used.

During the Focus Group Discussions (FGDs), two assistant moderators were assigned to systematically document participant inputs using structured note-taking techniques to capture key points, detailed arguments, and verbatim quotations. Immediately following each session, the assistants collaboratively reviewed and reconciled their notes. This process involved cross-verifying observations, resolving discrepancies, and consolidating insights to produce a single, comprehensive and finalized set of notes for each FGD.

Similarly, for the two in-depth interviews conducted in Lisbon, Portugal, one researcher led the conversation while the second focused on detailed note-taking. This collection of finalized, detailed notes from both the FGDs and in-depth interviews constituted the complete qualitative dataset. This dataset was then organized and served as the primary data for thematic analysis.

D. Data Analysis

1) CVI Analysis: The CVI analysis was employed to quantitatively assess the relevance of each task within the framework. Experts rated each task using a 4-point Likert scale, where 1 indicated "not relevant" and 4 indicated "highly relevant". Each task rated as 3 or 4 was converted to '1' to show that the rater finds the task relevant, and tasks rated as 1 or 2 were converted to '0' to show that the rater considers the task irrelevant.

For each task, the I-CVI was calculated using Eq. (1) by dividing the number of experts who rated the task as 1 by the total number of experts. The S-CVI/Ave as shown in Eq. (2) can be determined by averaging the I-CVI scores across all tasks [15]. The following are the formulas for the content validity index calculation:

$$I - CVI = \frac{Number\ of\ experts\ rating\ the\ item\ as\ "Relevant"}{Total\ number\ of\ experts} \quad (1)$$

$$S - CVI/Ave = \frac{\sum I - CVI}{Number\ of\ items\ in\ the\ component} \quad (2)$$

I-CVI with value of 0.78 or higher was considered acceptable for at least 9 raters, following the recommendations by Lynn [16]. For S-CVI/Ave value of 0.90 or above indicated excellent content validity, values between 0.80 and 0.89 suggested the need for minor revision, and values below 0.80 signalled the need for major revision or potential removal [15].

2) Thematic analysis: To explore participant's perspectives and experiences in depth, thematic analysis was conducted following the six-phase approach by Braun and Clarke [17]. Initially, the data were familiarized by reading and re-reading the transcribed FGDs and in-depth interviews. Next, initial codes were generated to identify significant features of the data relevant to the aim of the study and the enhancement of the proposed framework.

These codes were then organized into potential themes, which were reviewed and refined to ensure coherence and distinctiveness. Each theme was clearly defined and named to capture its essence accurately. Finally, a comprehensive report was produced, illustrating the themes with representative data extracts and providing a nuanced understanding of the participant's insights. This systematic approach facilitated a rich and detailed interpretation of the qualitative data.

IV. RESULT

This section presents the findings derived from the expert evaluation of the proposed ADiBA framework. The analysis incorporates both quantitative and qualitative data collected through the framework evaluation survey, FGDs, and in-depth interviews. The quantitative aspect was analyzed using the CVI to assess the relevance of each component and task within the framework. Meanwhile, qualitative insights obtained from open-ended survey responses and discussion sessions were subjected to thematic analysis to identify key themes, suggestions, and patterns in expert feedback. Together these findings informed the refinement and validation of the framework.

A. CVI Analysis

As per the established criteria, the content validity of the framework was assessed using the I-CVI and S-CVI/Ave. Table III presents the calculated I-CVI for each task, along the aggregated S-CVI/Ave for each component, and their corresponding interpretations based on the predefined threshold.

All the tasks achieved I-CVI values above 0.85, indicating strong agreement among experts regarding their relevance – except for two. The tasks "Remove Barriers" from Prepare Immersion of Analytical Culture component and "Develop Data Security, Privacy, Sharing, Ethics and Compliance Governance Framework" from Data Management and Governance component each scored an I-CVI of 0.77. However, given the minimal difference of 0.01 from the threshold, these tasks are still considered important and relevant. Therefore, rather than being removed, they are retained with minor revisions to improve clarity and better align them with their respective components.

TABLE III. SUMMARY OF I-CVI AND S-CVI/AVE VALUES WITH INTERPRETATION FOR FRAMEWORK COMPONENTS

Component	Task	Task Description (Task)	I-CVI	Interpretation
PREPARE IMMERSION OF ANALYTICS CULTURE	0.1	Create Urgency	0.85	Acceptable
	0.2	Build a Guiding Coalition	0.92	Acceptable
	0.3	Create a Vision for Change	0.92	Acceptable
	0.4	Communicate the vision	0.92	Acceptable
	0.5	Remove Barriers	0.77	Needs revision
	0.6	Create Short-Term Wins	0.85	Acceptable
	0.7	Build on the Change	0.85	Acceptable
	0.8	Anchor the change in the Organization's Culture	0.85	Acceptable
	S-CVI/Ave		0.87	Consider Minor Revision
BUSINESS UNDERSTANDING	1.1	Identify Business Goal	1.00	Acceptable
	1.2	Assess Situation	1.00	Acceptable
	1.3	Define Data Analytics goals or insights	1.00	Acceptable
	S-CVI/Ave		1.00	Component is Acceptable

DATA MANAGEMENT & GOVERNANCE	2.1	Data Governance Engagement Framework	0.85	Acceptable
	2.2	Define Data Governance Organization	0.85	Acceptable
	2.3	Develop Data Security, Privacy, Sharing, Ethics and Compliance Governance Framework	0.77	Needs revision
	S-CVI/Ave		0.82	Consider Minor Revision
PROJECT PLANNING	3.1	Identify Business Use Case	1.00	Acceptable
	3.2	Estimate Resources Required	0.92	Acceptable
	3.3	Perform Cost-Benefit Analysis	0.85	Acceptable
	3.4	Develop Project Plan	0.92	Acceptable
	S-CVI/Ave		0.92	Component is Acceptable
DATA UNDERSTANDING	4.1	Define Data Sources	1.00	Acceptable
	4.2	Design and Develop Data Sandbox	0.85	Acceptable
	4.3	Describe Data	1.00	Acceptable
	4.4	Develop Data Curation Engine	0.85	Acceptable
	4.5	Verify Data Quality	0.92	Acceptable
	S-CVI/Ave		0.92	Component is Acceptable
DATA PREPARATION	5.1	Extract Data	1.00	Acceptable
	5.2	Transform Data	1.00	Acceptable
	5.3	Explore and Visualize Data	0.92	Acceptable
	5.4	Modify Data	0.92	Acceptable
	S-CVI/Ave		0.96	Component is Acceptable
TOOL, TECHNOLOGY, AND INFRASTRUCTURE PROCUREMENT & PRESENTATION	6.1	Identify Required Tools, Infrastructure and Technology	0.92	Acceptable
	6.2	Evaluate Tools, and Technology	0.92	Acceptable
	6.3	Procure Tools	1.00	Acceptable
	S-CVI/Ave		0.95	Component is Acceptable
BUSINESS ANALYTICS MODELING	7.1	Identify Key Variables	0.92	Acceptable
	7.2	Select Modelling Techniques	0.92	Acceptable
	7.3	Design Test	0.92	Acceptable
	7.4	Build Model	0.92	Acceptable
	7.5	Assess Model	0.92	Acceptable
	7.6	Manage Model	0.92	Acceptable
	7.7	Deploy Model	0.92	Acceptable
	S-CVI/Ave		0.92	Component is Acceptable
DATA ANALYTICS PRODUCT DEVELOPMENT	8.1	Pre-Design Stage	0.92	Acceptable
	8.2	Design and Develop Dashboards	1.00	Acceptable
	8.3	Design and Develop Business Reports	1.00	Acceptable
	8.4	Develop Alerts	0.92	Acceptable
	S-CVI/Ave		0.96	Component is Acceptable
EVALUATION OF MODEL AND PRODUCT	9.1	Perform Data Product Testing	1.00	Acceptable
	9.2	Perform Pilot Test	1.00	Acceptable
	9.3	Prepare Test Report	1.00	Acceptable
Component	**Task**	**Task Description (Task)**	**I-CVI**	**Interpretation**
EVALUATION OF MODEL AND PRODUCT	9.4	Determine Next Course of Actions	1.00	Acceptable
	S-CVI/Ave		1.00	Component is Acceptable
DATA ANALYTICS PRODUCT DEPLOYMENT	10.1	Plan Deployment	1.00	Acceptable
	10.2	Plan Monitoring and Maintenance	1.00	Acceptable
	10.3	Report Final Results	1.00	Acceptable
	10.4	Review Project	1.00	Acceptable
	S-CVI/Ave		1.00	Component is Acceptable

MONITORING, MAINTENANCE, AND UPGRADES	11.1	Monitor Performance	1.00	Acceptable
	11.2	Correct Error	1.00	Acceptable
	11.3	Enhance Dashboard, Reports and Alerts	1.00	Acceptable
	11.4	Replace or Discard System if Obsolete	0.92	Acceptable
	S-CVI/Ave		0.98	Component is Acceptable
INCULTURATION OF BIG DATA ANALYTICS INTO BUSINESS	12.1	Generate Short-Term Wins	1.00	Acceptable
	12.2	Sustain: Build on the Change	1.00	Acceptable
	12.3	Anchor the Changes in the Organizational Culture	1.00	Acceptable
	12.4	Assess Impact of Big Data Analytics	1.00	Acceptable
	S-CVI/Ave		1.00	Component is Acceptable

All components recorded S-CVI values of 0.92 and above indicating excellent content validity, with the exception of two components. These two components – Prepare Immersion of Analytical Culture and Data Management and Governance had S-CVI/Ave values of 0.87 and 0.82, respectively. Based on the established interpretation range, these values fall within the 0.80-0.89 band, suggesting the need for minor revisions to enhance clarity or alignment with expert expectations.

From the result, it can be seen that experts provided almost 100% agreements for tasks toward the end of the framework component. It is uncertain whether these agreements reflect genuine perceptions of task relevance, or if they may have resulted from experts becoming fatigue and thus responding less critically or attentively. This introduces a potential bias in the data, as some responses may not fully reflect the experts' considered judgment.

While potential response fatigue cannot be entirely ruled out, the overall results of the CVI analysis indicate that the framework is considered relevant and appropriate by the expert panel. The high I-CVI and S-CVI/Ave values across the majority of tasks and components reflect strong agreement among experts on the framework's content validity.

B. Thematic Analysis

Thematic analysis was conducted to explore expert insights and experiences relevant to each component of the proposed framework. Qualitative data were drawn from open-ended survey responses, FGDs, and in-depth interviews. The thematic analysis revealed specific implementation challenges, enablers, and suggestions, which were mapped against the framework's components to guide further refinement. To ensure clarity and relevance, the thematic analysis findings are organized by the components of the proposed framework, enabling detailed exploration of expert perspectives within each specific area.

1) Thematic analysis by components: For Prepare Immersion for Analytics Culture component, experts highlighted a range of critical improvements and areas requiring clarification. Several experts found that the tasks in this component closely overlap with those in the next component (Business Understanding), leading to confusion, and suggested either merging the two or switching the order to better reflect their purpose. A key recommendation was to establish the data governance team at the outset, before any framework activity begins, to provide strategic direction and oversight. Creating a sense of urgency was another frequently mentioned point, with recommendations to include lessons learned or prior failures as motivation. There was concern over when to conduct maturity and adoption assessments, and a suggestion that these be used at multiple points – before and during framework application as a way to tailor next steps. In summary, Prepare Immersion for Analytics Culture requires clearer structure, stronger leadership components, an emphasis on culture and urgency, and better integration with the broader framework cycle.

Expert feedback on Business Understanding component revealed critical insights on refining the strategic foundation and ensuring the component sets a strong direction for the entire framework. Many experts suggested switching Business Understanding component with Prepare Immersion for Analytics Culture component, as Business Understanding is seen as an essential first step. There was a strong push to include a comprehensive maturity assessment covering both people and infrastructure technology to better inform the organization's readiness for BDA. Experts also recommended defining BDA roadmap under this component and starting with clear enterprise-level goals before diving into specific roles or committee structures. Several comments stressed the importance of clearly identifying the pain point, using tools such as SWOT analysis and impact analysis to understand business challenges and opportunities. Benchmarking with competitors in similar industries was encouraged to help organizations understand where they stand and what best practices to adopt. Feedback also suggested shortening unnecessary early-stage activities such as analysis of contractors and consultants, and instead focusing on the critical success factors and a forward-moving plan. Sustainability and cultural buy-in were also emphasized, with a need to motivate ongoing engagement. Overall, Business Understanding needs clearer guidance, stronger business alignment, and a practical approach to managing constraints while still establishing a solid business case for data-driven transformation.

For Data Governance and Management component, expert feedback emphasized the importance of establishing a clear and adaptive governance structure. Experts suggested that the data organization model whether centralized, decentralized, or hybrid must be well-defined, including distinctions between ICT-driven and business driven models, as well as the roles of data engineers versus data scientists. Additionally, there is a need to provide clear references and guidance on how to structure and assign roles within data governance councils or teams, such as owners, stewards, and risk officers, in alignment with organizational data maturity. There was also concern about ownership and accountability, particularly regarding the role of data owners and the need to clarify whether this overlap with roles like a data sponsor. Ownership of the data governance framework whether it belongs to the strategy team or data owners, was seen as critical, especially in government contexts where BDA initiatives typically span multiple ministries and agencies. In multi-agency environments, initial agreements often break down when data sharing becomes contentious. This highlighted the need for strategic teams to oversee framework implementation and anticipate political and administrative challenges.

The Project Planning component received expert suggestion focusing on the need for refining task structures and sequencing. There were suggestions to reorganize subtasks – some could be moved to other components, while others could be combined or removed if already addressed elsewhere. Additionally, experts emphasized the importance of well-defined project implementation plan, including risk assessment analysis, which would improve preparedness and help mitigate uncertainties during the execution of BDA projects. A key point raised was the importance of prioritizing platform versus data readiness. Experts questioned which should come first in BDA projects, urging the need for clear guidance based on project context.

In relation to the Data Understanding component, experts pointed out the importance of the foundational role of infrastructure readiness, with multiple reviewers asserting that data understanding activities can only proceed effectively once platforms and data architecture are clearly defined. The need to define data source characteristics and behaviour emerged strongly, including guidance on metadata management, crawler/scraper tools, and the handling of data based on SOPs and business process. Several experts stressed the importance of data profiling and exploratory analysis before attempting data quality checks, citing practices such as measuring missing values and data health status. Data curation engine was recommended to be reframed as “digitalization”, and data ingestion was suggested as a better term, than merely defining data sources. In addition, experts emphasized developing small-scale lake and ensuring that machine-readable formats are prioritized for open data and sharing purposes. Lastly, confusion about the term “data sandbox” was raised, suggesting a need to revise or clearly define it in the framework.

Feedback from experts on the Data Preparation component emphasized the importance of adopting a more agile and iterative approach, with some suggesting that integrating DataOps principles could enhance the adaptability of this phase. A major point raised was the logical sequencing of tasks – experts noted that data processing should be addressed before initiating data exploration and visualization. There were also concerns about task allocation, with the observation that feature engineering might be more appropriate under the Business Analytics Modelling component rather than the current stage. Experts encouraged refining this component to avoid redundancy, especially concerning data validation and missing values, which they noted are already examined in the data understanding phase. These insights point toward the need to streamline the Data Preparation process and ensure that each sub-task is placed in the most relevant component to avoid duplication and confusion.

For the Tool, Technology, and Infrastructure Procurement and Presentation component, experts highlighted a key gap in the component: while the current focus is on tools, there is an evident lack of attention to infrastructure and technology elements. There was a string consensus on the need to expand this component to include implementation activities such as setting up the big data platform after tool procurement, and proof of concept execution using real business cases to validate feasibility. In light of current digital threats, experts recommended integrating cybersecurity requirements both during tool evaluation and procurement, ensuring security compliance and closing potential loopholes. Additionally, while some suggested merging this component with Project Planning, others were open to keeping it separate, provided that the scope is clearly defined and comprehensive.

Experts input on Business Analytics Modelling component suggested the importance of continuous improvement and clarity of expected outcome. One key theme that emerge was the need to ensure that the analytics models remain accurate and relevant when applied newly incoming datasets. Additionally, experts highlighted the need to include expected results or anticipated outcomes of each modelling task.

For the Data Analytic Product Development, experts pointed three key areas of enhancement. First, they noted that time-series visualizations are integrated and aligned with industry standards. Second, experts recommend exploring non-linear dashboard layouts, which break away from traditional grid-based or sequential flows. Lastly, there was a suggestion to incorporate data modelling directly within the dashboard development process.

For the Evaluation of Model and Product, experts revealed several areas of confusion and suggestions for improvement. A recurring theme was the structural clarity of the evaluation component, particularly the placement of model evaluation and product evaluation. Experts questioned whether model evaluation should be integrated as a subphase under Business Analytics Modelling component, as they are closely connected. Similarly, product evaluation, if it refers to dashboard, was suggested to be part of the Data Analytics Product Development component. Furthermore, the importance of practical evaluation strategies was emphasized, recommending the inclusion of a proper test plan, diverse testing approaches, and migration strategies to ensure smooth deployment.

For the Data Analytic Product Deployment component, experts suggested that the inclusion of a clear roll-out plan to ensure the smooth implementation of big data initiatives across the organization.

Feedback on the Monitoring, Maintenance, and Upgrades component emphasized the importance of providing a scalable infrastructure that can accommodate future growth in data volume and processing needs.

Finally, for the Inculturation of Big Data Analytics into Business component, experts highlighted the need for continuous efforts to embed analytics practices within organizational culture. Experts suggested conducting a post-maturity assessment to monitor progress, implementing ongoing campaigns or awareness programs focusing on data-related challenges, and organizing regular checkpoint meetings by the steering or working committee to track developments. Moreover, performing impact analysis simulations and identifying "quick wins" alongside medium-term plans were highlighted to sustain momentum and demonstrate early value in the adoption of BDA.

The summarized thematic analysis for each component according to themes can be seen in the following Table IV.

TABLE IV. SUMMARY OF THEMATIC ANALYSIS BY THEME AND ITS COMPONENTS

Theme	Relevant Component	Key Issues	Expert Suggestions
Sequencing and Structural Clarity	Prepare Immersion for Analytics Culture, Business Understanding, Project Planning, Evaluation of Model and Product	Overlap between components; unclear starting point; misplaced tasks or evaluations	Switch or merge components 1 & 2; clearly define sequence of tasks; move evaluation activities under appropriate phases (e.g., modelling or dashboard development)
Governance and Role Clarity	Prepare Immersion for Analytics Culture, Business Understanding, Data Governance and Management,	Undefined roles; lack of ownership and accountability; unclear governance models	Define centralized/decentralized/hybrid models; assign clear roles (owners, stewards); establish governance team early
Readiness and Maturity Assessment	Prepare Immersion for Analytics Culture, Business Understanding, Inculturation of Big Data Analytics into Business	Readiness not assessed early or revisited	Conduct people + tech maturity assessments at start and mid-cycle; use post-maturity assessments after implementation
Cultural Embedding and Change Management	Prepare Immersion for Analytics Culture, Business Understanding, Inculturation of Big Data Analytics into Business	Weak emphasis on change culture and ongoing motivation	Create urgency using past lessons; embed campaigns and checkpoint meetings; track quick wins and momentum
Infrastructure and Platform Readiness	Data Understanding, Tool, Technology, and Infrastructure Procurement and Presentation, Monitoring, Maintenance, and Upgrades	Underdeveloped infrastructure focus; unclear timing for platform readiness	Address infrastructure before data work; add infra setup post-procurement; ensure scalability for growth
Agile and Iterative Practice	Data Preparation, Business Analytics Modelling, Data Analytic Product Development	Phases too linear or redundant; lack of agility	Apply agile/DataOps principles; reposition feature engineering; make components more iterative and streamlined
Security and Risk Management	Project Planning, Tool, Technology, and Infrastructure Procurement and Presentation,	Cybersecurity missing; risk planning weak	Add cybersecurity criteria to procurement; include risk analysis in planning
Output Clarity and Evaluation	Business Analytics Modelling, Data Analytic Product Development, Evaluation of Model and Product	Lack of clarity on expected outcomes; unclear evaluation scope	Define expected model results; create test/migration plans; relocate product evaluation to correct phase
Visualization and Usability	Data Analytic Product Development	Rigid layout; missed integration opportunities	Adopt time-series and non-linear dashboard options; embed modelling directly into visual design
Deployment Planning and Execution	Project Planning, Data Analytic Product Deployment	No clear roll-out plan; poor execution readiness	Define deployment steps; align platform/data readiness before execution
Data Quality and Profiling	Data Understanding, Data Preparation	Redundancy and poor sequencing of data checks	Emphasize data profiling before validation; avoid duplicate quality tasks across components

1) Thematic analysis of overall framework: Overall, experts revealed several critical themes that reflect both structural and practical challenges. One of the most pressing concerns was clarity and connectivity within the framework. Experts noted that the framework appeared disjointed, with unclear linkages between components. This lack of cohesion made it difficult for users to understand how the process flows from one stage to the next or how long each stage might take. The absence of a defined timeline or lifecycle for the framework components further compounded this issue, leading to suggestions for a clearer depiction of the overall process, including estimated durations and interdependencies.

The usability and agility of the framework were also scrutinized. Experts emphasized the importance of incorporating flexible decision-making mechanisms, particularly for context where data availability is limited or governance issues arise. This aligns with concerns that BDA adoption often fails due to an overemphasis on technology, while underestimating organizational and cultural aspects. To counter this, there were calls for more agile and adaptable framework that could accommodate varying entry points depending on an organization's maturity level or existing infrastructure.

Experts highlighted that the tools and instruments included in the framework appeared standard and more appropriate for beginners. However, they recommended that these tools be better integrated across the components to ensures continuity and support scalability. A particular emphasis was placed on improving the clarity and usability of some instruments, which were seen as difficult to interpret or complete without guidance.

Another recurring theme was the importance of infrastructure readiness. Multiple experts emphasized that infrastructure should be fully in place prior to initiating BDA projects, particularly in environments where phased implementation may not be viable. This was tied to the broader issue of platform and use case development, both of which were deemed essential before launching analytics activities.

Organizational roles and structure emerged as a key theme, with experts stressing the need for two distinct but collaborative working teams – data scientists and data engineers. Moreover, a dedicated BDA team should be assigned exclusively to analytics work, without being burdened by unrelated tasks.

A strong leadership structure was considered vital, with top-down instructions and the appointment of BDA champions cited as enablers of successful implementation. In the absence of leadership or designated champions, enculturation and sustained adoption were identified as areas of concern.

Lastly, experts noted that the “early components” of the framework particularly problem identification were the most challenging. This was attributed to organizations lacking clarity in articulating business problems or use cases. Some experts proposed incorporating an “as-is/to-be” study at the beginning to define current capabilities and desired outcomes more effectively.

The summarized thematic analysis for overall framework according to themes can be seen in the following Table V.

TABLE V. SUMMARY OF THEMATIC ANALYSIS OF THE OVERALL FRAMEWORK

Theme	Expert Insights and Suggestions
Clarity and Connectivity	Framework components appeared disjointed; unclear linkages and lack of flow between stages. Suggested inclusion of process flow, interdependencies, and estimated timelines.
Usability and Agility	Need for more flexibility in the framework to accommodate varied contexts, such as low data maturity or limited infrastructure. Recommends support for different entry points.
Tools and Instruments	Tools included were seen as basic; need to enhance integration across components and improve usability. Some instruments required more guidance or simplification.
Infrastructure Readiness	Strong emphasis on ensuring infrastructure and platforms is in place before initiating BDA work. Phased implementation is not always suitable.
Organizational Structure	Clear roles needed: separate data scientists and data engineers, with a dedicated BDA team. Leadership and BDA champions essential for sustained adoption and success.
Leadership and Culture	Top-down support and cultural readiness critical. Lack of leadership seen as a barrier to adoption and long-term success.
Early-Stage Complexity	Early framework stages, especially problem identification, were most difficult. Suggested including an "as-is/to-be" study to better define current state and future goals.

The expert feedback underscores the importance of refining the framework to enhance its practical applicability and ensure it can support diverse organizational contexts and maturity levels. These insights directly inform the subsequent framework enhancement process.

V. ADiBA Framework Enhancement

Based on the CVI and thematic analyses, the ADiBA framework underwent significant enhancements. While the framework still retained its thirteen core components, these revisions strategically refined its overall structure and significantly modified the underlying components and tasks, thereby improving its suitability for broader application. Specifically, feedback informed meticulous modifications, with components and tasks being added, revised, or removed to enhance clarity, eliminate redundancy, and integrate actionable assessment points. The details of these integrated enhancements are provided below, with the finalized visual representation of the ADiBA framework and its update components presented in Table VI and Fig. 2 at the end of this section.

For the first component, the name Prepare Immersion of Analytics Culture was changed to Enterprise Big Data Analytics Preparation for better and clearer purposes. Two new tasks were added to the component: Set up Strategic Planning Team [18], and Perform Internal Situation Analysis [10], [19], [20], [21], [22], [23], [24]. Setting up teams responsible for steering, planning and monitoring Big Data Analytics adoption and implementation in organizations is essential to ensure data initiatives align with overall business objectives. The team will consider the people, processes, and data infrastructure involved and guide the organization toward data-driven goals. Although the experts suggested that setting up the data governance team must be established early before any framework activities can be conducted, it is more important to set the strategic planning team to oversee the whole BDA implementation. The task “Performing an Internal Situation Analysis” is introduced to address the expert’s recommendation to define specific points in the framework for conducting maturity and adoption assessment, especially before its application. This task includes sub-tasks such as administering surveys to assess the organization’s structure and to identify key personnel who can provide accurate insights into the organization’s data and analytics maturity. Additionally, it enables the organization to pinpoint existing gaps in skills and capabilities. This is crucial because possessing technical skills alone does not guarantee effective execution; some individuals may have the required skills but the lack of contextual understanding or practical ability to perform tasks effectively. This task was also introduced to address redundancy with a similar task “Assess Situation” in the Business Understanding component. The overlapping task in Business Understanding component will be removed to avoid duplication and ensure a clearer, more streamlined activities within the framework. To strengthen the leadership aspects within this component, a subtask related to securing leadership commitment was added under task “Build a Guiding Coalition” to ensure active commitment and visible support from executive leaders to champion the BDA initiatives. Based on the CVI analysis, the “Remove Barriers” task received a rating below the acceptable threshold, indicating that some experts questioned its clarity and relevance. Rather that removing the task entirely, it was retained and refined to address these concerns. The task now includes a more specific focus on the types of barriers that commonly hinder BDA readiness, and outlines actionable strategies for overcoming these barriers. To improve more on the clarity and focus of this component, two tasks “Build on the Change” and “Anchor the Change in the Organization's Culture” were removed, as they were redundant with tasks included in the final component of the framework – Data Analytics Product Enculturation.

TABLE VI. ENHANCED ADIBA FRAMEWORK COMPONENTS AND TASKS

No.	Enhanced Framework		
	Component	***Task***	
1	ENTERPRISE BIG DATA ANALYTICS PREPARATION	BDAP.1	Set up Strategic Planning Team
		BDAP.2	Perform Internal Situation Analysis
		BDAP.3	Create a Sense of Urgency
		BDAP.4	Build a Guiding Coalition
		BDAP.5	Form Strategic Vision and Initiatives
		BDAP.6	Enlist a Volunteer Army
		BDAP.7	Remove Barriers
		BDAP.8	Generate Short-Term Wins
2	BUSINESS UNDERSTANDING	BU.1	Identify Business Goal
		BU.2	Analyse Strategic Context and Organizational Structure
		BU.3	Define Data Analytics Goals or Insights
3	PROJECT PLANNING	PP.1	Identify Business Use Case
		PP.2	Perform Cost-Benefit Analysis
		PP.3	Develop Project Plan
4	DATA GOVERNANCE	DG.1	Define Data Governance Organization
		DG.2	Develop Data Security, Privacy, Sharing, Ethics and Compliance Governance Framework
		DG.3	Define Data Quality Process
5	DATA AND ANALYTICS REPOSITORY MANAGEMENT	DARM.1	Data Ingestion
		DARM.2	Design and Develop Enterprise Single Source of Truth Master Data Management
		DARM.3	Develop Enterprise Metadata Hub
		DARM.4	Verify and Implement Data Quality
		DARM.5	Incorporate New Data Request
		DARM.6	Maintain Data Analytics Inventories
6	TOOL, TECHNOLOGY, AND INFRASTRUCTURE PROCUREMENT & PREPARATION	TTIP.1	Identify Required Tools, Technology, and Infrastructure
		TTIP.2	Evaluate Tools, Technology, and Infrastructure
		TTIP.3	Procure and Prepare Tools, Technology, and Infrastructure
7	DATA ANALYTICS VISUALIZATION DEVELOPMENT	DAVD.1	Pre-Design Stage
		DAVD.2	Design and Develop Dashboards
8	DATA ANALYTICS PRODUCT MODELING	DAPM.1	Identify Key Variables
		DAPM.2	Select Modelling Techniques
		DAPM.3	Perform Data Sampling
		DAPM.4	Feature Engineering
		DAPM.5	Build Model
		DAPM.6	Assess Model
		DAPM.7	Manage and Deploy Model
9	DATA PREPARATION	DP.1	Identify Data Requirements and Extract Data
		DP.2	Explore and Transform Data
		DP.3	Publish Data
10	DATA ANALYTICS PRODUCT EVALUATION	DAPE.1	Perform Dashboard Testing
		DAPE.2	Prepare Evaluation Report and Next Course of Action
11	DATA ANALYTICS PRODUCT DEPLOYMENT	DAPD.1	Deploy Dashboard
		DAPD.2	Perform Stress Test

		DAPD.3	Document the Data Analytics Product
12	DATA ANALYTICS PRODUCT MONITORING, MAINTENANCE AND UPGRADES	MMU.1	Plan the Performance Monitoring
		MMU.2	Correct Any Errors
		MMU.3	Enhance Dashboards
		MMU.4	Replace or Discard Dashboards if Obsolete
No.	**Enhanced Framework**		
	Component	***Task***	
13	DATA ANALYTICS PRODUCT ENCULTURATION	DAE.1	Sustain the Changes
		DAE.2	Anchor the Changes in the Organizational Culture
		DAE.3	Assess Impact of Big Data Analytics

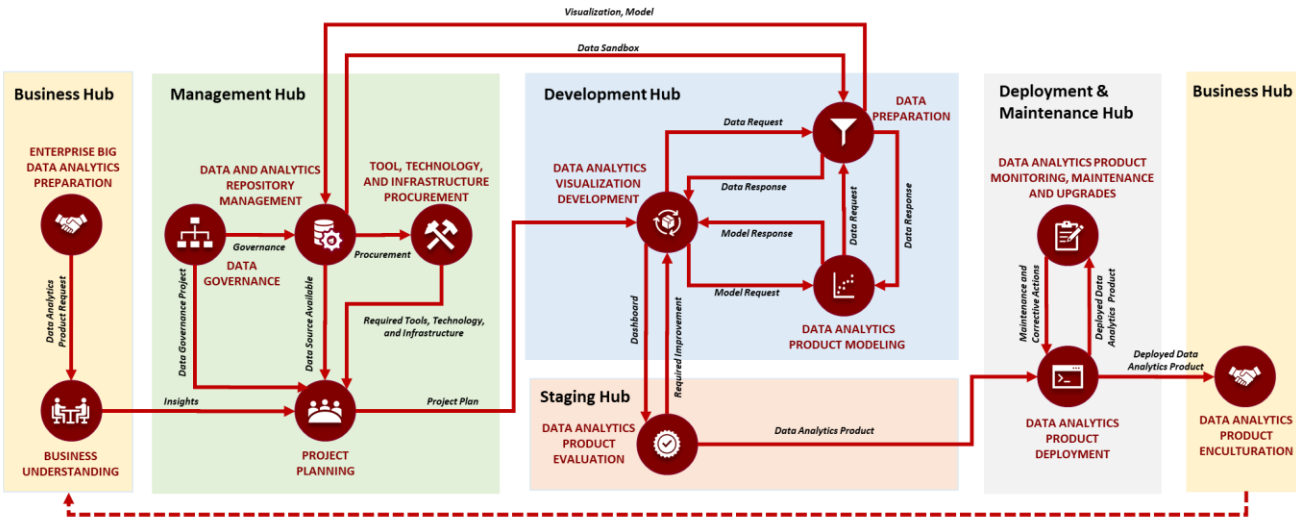

Fig. 2. Enhanced visual representation of the ADiBA framework.

For the Business Understanding component, the task previously titled "Assess Situation" was renamed to "Analyse Strategic Context and Organizational Structure" to avoid confusion with another existing task, "Perform Internal Situation Analysis" in Prepare Immersion of Analytics Culture component. Although both tasks involve forms of assessment, their focus and content are distinct. "Perform Internal Situation Analysis" task emphasizes understanding the organization's current structure, readiness, and maturity in data and analytics, often through surveys or interviews. In contrast, the renamed task focuses on analysing strategic elements such as the organization's goals and objectives, SWOT analysis, roles and responsibilities, customer charter, and key performance indicators. Following expert feedback, the task "Identify Business Goals" was enhanced to include the definition of critical success factors. The more extensive development of solid business cases as recommended by experts, has been comprehensively integrated into the Project Planning component.

The Data Management and Governance component was changed to Data Governance as the tasks were more aligned with governance-related activities. Additionally, the "Data Governance Engagement Framework" task was removed due to overlap with "Define the Data Governance Organization", particularly in role and structure definition. Based on expert feedback, several enhancements were made to strengthen the "Define the Data Governance Organization" task. This task now incorporates outlining the roles of data engineers versus data scientists within the governance structure, and assigning responsibilities within data governance councils or teams. Furthermore, it addresses ownership and accountability, especially in distinguishing the roles of data owners and sponsors, and defines who should own the governance framework – whether it is the strategy team or data owners in both single and multi-agency contexts. Political and administrative challenges in multi-agency environments are acknowledged, and the role of strategic teams in overseeing governance framework implementation is emphasized. The task "Develop Data Security, Privacy, Sharing, Ethics and Compliance Governance Framework" received a CVI rating below the threshold, indicating a need for refinement. Although no explicit justification was provided by the experts, the low rating may be dues to the task's broad scope and lack of practical guidance. To address this, several subtasks were included such as identifying applicable data protection laws and regulations; define policies for data access, classification, and retention; and establish ethical guidelines for analytics. A new task, "Define the Data Quality Process" [10] was added to strengthen the component's foundation. The task focuses on data quality requirements and improvement programs and preparing data quality tests that cover all data quality dimensions: completeness, conformity, consistency, accuracy, uniqueness, integrity, validity, and timeliness. This is to ensure data quality is a critical element of data governance, as it supports reliable data for analytics and decision-making.

The Project Planning component has been strengthened to provide a more comprehensive approach to developing project plans. This was achieved by combining the formerly separate "Estimate Resources Required" and "Perform Cost-Benefit Analysis" tasks into a unified process. This is to ensure that resource allocation is directly informed by a thoroughly financial and practical assessment. Furthermore, the updated "Develop Project Plan" task now explicitly incorporates a well-defined project implementation plan and integrates comprehensive risk assessment analysis, ensuring all potential challenges are identified and addressed proactively within the planning phase.

The Data Understanding component has undergone a comprehensive transformation, now formally established as Data and Analytics Repository Management. This strategic evolution underscores a deeper focus on not just comprehending data, but actively managing it within a robust repository environment, which emphasizes on infrastructure readiness for all subsequent data activities. This component's tasks have been meticulously refined and expanded. The initial task, formerly known as "Define Data Sources" has been reconceptualized as "Data Ingestion", which now provides guidance on defining intricate data source characteristics and behaviour, and strategically incorporates the use of crawler/scraper tools for efficient and structure data acquisition. The "Design and Develop Data Sandbox" task was renamed to "Design and Develop Enterprise Single Source of Truth Master Data Management" [25]. This is to detail the design and development of enterprise-wide data consistency frameworks, including data warehouses, data marts, data lakes, and integrated enterprise master data management with robust integrity checks. The "Describe Data" task was changed to "Develop Enterprise Metadata Hub" [26] to define data's metadata and incorporate advanced metadata management strategies for enhanced discoverability and governance. The experts suggested to change the "Develop Data Curation Engine" task to "Digitalization", but it seems to be too broad and abstract for a specific task. The subtasks described under this task align closely with what is now covered under the "Data Ingestion" task. Therefore, to ensure clarity and avoid redundancy within the component, the most logical approach would be to fully incorporate the development of data extraction engines / data input portals / data capturing systems directly into the "Data Ingestion" task. Significant enhancements have been made to the task "Verify and Implement Data Quality" as detailed by [10], [20], [22], [23], [27], [28], [29], [30], [31], and [32]. Organizations can identify the data quality requirements and their problems and implement the data quality measures and problem rectification. Two new tasks were added to this component: Incorporate New Data Requests and Maintain Data Analytics Inventories. Both designed to ensure continuous and managed growth of the data and analytics repository. Throughout all tasks, there is a clear prioritization of machine-readable formats to facilitate open data and efficient sharing, further enhancing the utility and accessibility of the managed data assets.

The tasks remained the same for the Tool, Technology, and Infrastructure Procurement & Presentation component. The only changes that were made were to the component and task names to make the purposes much more straightforward. The scope was broadened to include infrastructure and technology elements, moving beyond just tools to encompass he entire foundational environment.

The Data Analytics Visualization Development component, formerly "Data Analytics Product Development", has been refined to focus on creating impactful visual outputs. The tasks "Design and Develop Business Reports" and "Develop Alerts" were merged into "Design and Develop Dashboards" task.to further enhance this component, the "Design and Develop Dashboards" tasks now explicitly ensures that time-series visualizations are integrated and aligned with industry standards, providing clear insights into trends over time. This task also encourages exploring and suggesting non-linear dashboard layouts to create more intuitive and engaging user experiences.

The Data Analytics Product Modelling component, previously known as Business Analytics Modelling, has undergone a focused enhancement to better reflect its purpose and incorporate crucial best practices. While retaining its core responsibilities, the component now explicitly includes a vital new task: Feature Engineering [33]. This process encompasses feature extraction, selection, or reduction, and data augmentation as needed, significantly enriching the data preparation for model building. The "Design Test" task has also been refined and renamed to "Perform Data sampling", where data from the prepared sandbox is strategically selected and split into training and testing sets, with option to perform bootstrapping if the sample size is insufficient. To ensure models remain accurate and relevant over time, the need for continuous improvement within the "Manage and Deploy Model" task is emphasized. This ensures ongoing monitoring and recalibration as new data emerges. Additionally, the "Select Modelling Techniques" and "Build Model" tasks now require the definition of expected results or anticipated outcomes.

For the Data Preparation component, the initial "Extract Data" task has been expanded and renamed to "Identify Data Requirements and Extract Data", a task highlighted by [10], [34], and [35], emphasizing the crucial step of defining data needs before extraction. The workflow is streamlined by merging the "Transform Data" and "Explore and Visualize Data" into a single, comprehensive task: "Explore and Transform Data". This task is now central to preparing data for machine readability, which includes steps such as exploring data, cleaning data, transforming data, identifying and treating missing values, detecting and treating outliers, normalizing data, and tagging and annotating data. While "Feature engineering" has been re-evaluated and primarily moved to the Data Analytics Product Modelling component to avoid redundancy, data validation and the handling of missing values remain firmly within the "Explore and Transform Data" to prevent overlap with the Data and Analytics Repository Management component. The redundant "Modify Data" task was removed, and a new "Publish Data" task was introduced to ensure prepared data is readily available to requesters in a data sandbox.

The Data Analytics Product Evaluation component, previously known as “Evaluation of the Model and Product”. Has been refined to streamline its processes and enhance clarity. We’ve consolidated the original tasks into two comprehensive steps: “Perform Dashboard Testing” and “Prepare Evaluation Report and Next Course of Action”. The “Perform Dashboard Testing” task now integrates component testing, analytic product testing, and crucial user acceptance and satisfaction testing, ensuring a thorough assessment. These diverse testing approaches include a broader range of validation techniques. While model evaluation is now considered for integration into the Data Analytics Product Modelling component, and dashboard-specific product evaluation might align with Data Analytics Product Development to avoid redundancy, this component retains its focus on overarching product validation. For the “Prepare Evaluation Report and Next Course of Action” task, defects are recorded, potential actions identified, and a final decision is made regarding product deployment. The task also includes essential guidance on migration strategies for smooth deployment, ensuring a seamless transition for the product.

For the Data Analytics Product Deployment component, the “Plan Monitoring and Maintenance” task was strategically moved to a subsequent component focused on ongoing monitoring activities, allowing this stage to concentrate purely on deployment. The “Deploy Dashboard” task includes the development of a clear roll-out plan for organization-wide implementation. A new critical task, “Perform Stress Test” was added to evaluate the dashboard’s performance and stability under extreme or heavy loads. Additionally, the “Report Final Results” and “Review Project” tasks were merged into a single, comprehensive task: “Document the Data Analytics Product”, ensuring all relevant information is captured.

The Monitoring, Maintenance, and Upgrades component has been refined and renamed to Data Analytics Product Monitoring, Maintenance, and Upgrades. This change clarifies that its focus solely on the data analytic product, not the entire ADiBA framework. While the core responsibilities remain consistent, the task names were updated for better clarity. The further enhance this component, the “Plan the Performance Monitoring” task now emphasizes the importance of a scalable infrastructure to accommodate future growth. The other tasks, “Correct any Errors”, “Enhance Dashboards”, and “Replace or Discard Dashboards if Obsolete”, continue to ensure the long-term reliability and effectiveness of the data analytics product.

The Inculturation of Big Data Analytics into Business component has been refined and renamed to Data Analytics Product Enculturation, more accurately reflecting its purposes of embedding data analytics within the organization. While the core tasks remain, “Generate Short-Term Wins” was removed to avoid repetition with the earlier component. The finalized tasks are now: “Sustain the Changes”, “Anchor the Changes in the Organizational Culture”, and “Assess Impact of Big Data Analytics”. The “Sustain the Changes” task now emphasizes continuous efforts to embed analytical practices and includes organizing regular checkpoint meetings by the steering and working committee to maintain momentum. For “Anchor the Changes in the Organizational Culture” task, the need for ongoing campaigns or awareness programs focusing on data-related challenges was integrated, fostering a data-driven mindset throughout the organization. Finally, the “Assess Impact of Big Data Analytics” task is strengthened by the inclusion of conducting a post-maturity assessment and performing impact analysis simulations, allowing a comprehensive evaluation of the analytics product’s effectiveness and organizational transformation.

The ADiBA framework has undergone substantial refinement, building on its initial reorganization. While the framework still retains its thirteen core components, significant changes were made to their individual tasks and broader component definitions to enhance its effectiveness. These components are now strategically grouped into five distinct hubs – Business, Management, Development, Staging, and Deployment & Maintenance – to differentiate the phases and gather related functions, thereby improving process flow and logical alignment. The visual representation of the ADiBA framework can be seen in Fig. 2.

The revised framework begins with the Enterprise Big Data Analytics Preparation component, which outlines steps to prepare the organization for a data-driven culture. This preparatory stage is now implicitly strengthened by the expert emphasis on strong leadership, top-down instructions, and the formation of a dedicated BDA team (comprising distinct data scientists and data engineers), all crucial for effective enculturation. The deliverable of this component is the data analytics product requested by the organization. Next, the Business Understanding component helps organizations articulate their goals and problems, ensuring BDA delivers desired values and empowers decision-making. Critically, to address challenges in early problem identification, this component is now enhanced by incorporating an “as-is/to-be” study to more effectively define current capabilities and desired outcomes.

The Data Governance, Data and Analytics Repository Management, and Tool, Technology, and Infrastructure Procurement & Preparation components can be conducted concurrently, established and managed independently of specific BDA projects. These activities generate the overarching data governance project, detailed insights on available data assets, and the necessary tools, technologies and infrastructure. They thus serve as enabling pillars that support any subsequent BDA initiatives integrated within this framework. Furthermore, based on expert feedback, the framework now explicitly states that infrastructure should be fully in place prior to initiating BDA projects, particularly in environments where phased implementation isn’t viable.

Organizations then use this strengthened information to plan the project through the Project Planning component. The project plan moves into the Development Hub, which includes Data Analytics Visualization Development, Data Analytics Product Modelling, and Data Preparation. These processes are iterative, ensuring the efficient development of the dashboard along with its underlying data and analytics model. This iterative approach now explicitly embodies the framework’s enhanced usability and agility, integrating flexible decision-making mechanisms particularly relevant for context with limited data availability or governance issues, and allowing for varying entry points based on organizational maturity.

Following development, dashboards undergo various testing in the Data Analytics Product Evaluation component before being deployed via the Data Analytics Product Deployment component. The Data Analytics Product Monitoring. Maintenance, and Upgrades component handles ongoing corrections or enhancements. Finally, the Data Analytics Product enculturation component outlines steps to embed the data analytics into business practices. This final stage is directly supported by the framework's emphasis on fostering strong leadership and the role of the BDA champions, ensuring the sustained adoption and cultural anchoring of BDA within organization.

Ultimately, these enhancements directly address the challenges highlighted by experts, forging a BDA implementation framework that is clearer, more agile, and more comprehensively integrated. The result is a more practical and effective guide for organizations navigating their data analytics journey.

VI. Conclusion

Recognizing the necessity for a structured pathway in BDA implementation in organizations, this study undertook the enhancement of the existing ADiBA framework. Initially developed through systematic literature review, the framework's refinement process involved a comprehensive mixed-methods survey. Domain experts provided quantitative feedback via a five-point Likert scale, which was then assessed using the CVI against an I-CVI threshold of 0.78. parallel to this, qualitative data from open-ended questions, FGDs, and in-depth interviews were subjected to thematic analysis, revealing key insights into the framework's clarity and practical application. The integration of these empirical findings directly guided the strategic adjustments made to the framework's various components.

This study makes a significant contribution by transforming a theoretically derived framework into an empirically validated and refined guide for BDA implementation. The enhances ADiBA framework offers organizations a robust and expert-informed tool to navigate the complexities of becoming data-driven, potentially accelerating digital transformation efforts and improving decision-making process. Theoretically, this research contributes to the body of knowledge on framework development and validation methodologies in the context of information systems.

While this study refined the ADiBA framework based on expert insights, it is important to acknowledge that the validation was primarily based on expert perception. Practical application and studies over time are essential for a full assessment of its efficacy.

Looking ahead, the next crucial step involves a more comprehensive verification of the enhanced ADiBA framework through real-life case studies within actual organizations. The plan is to identify several organizations currently undertaking BDA projects and guide them through the enhanced ADiBA framework's components. By integrating the framework into their existing processes, its practical utility and impact on their journey to becoming data-driven entities can be observed. From these case studies, in-depth feedback will be collected from organizational stakeholders regarding the framework's applicability, ease of use, and effectiveness in addressing their BDA challenges. This practical application will provide valuable insights into its efficacy and adaptability in diverse operational contexts, further strengthening its utility for BDA implementation and leading to subsequent rounds of refinement.

Beyond these immediate plans, potential avenues for future exploration include extending the ADiBA framework to incorporate emerging technologies like Artificial Intelligence (AI) and Machine Learning (ML) integration strategies. Further research could also investigate the framework's applicability across different industry sectors or organizational sizes, as well as developing a digital tool or assessment instrument based on the framework to aid organizations in self-assessing their BDA readiness.

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