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Frameworks for Business Value Creation Enabled by Business Intelligence & Analytics

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Abstract— The ability to convert raw data into business value can be used in the modern digital economy as the hallmark of market leadership. The report provides an in-depth analysis of theoretical and practical frameworks that allow organisations to derive tangible value out of Business Intelligence (BI) and Business Analytics (BA). We explore the organisational development of the analytical maturity levels, the dynamics of information development through the organisational structure and the factors that are critical in the alignment of technical capabilities to strategic goals.

The analysis is a synthesis of some of the most pronounced models on the industry like the Gartner Analytic Ascendancy Model, the SAS Information Evolution Model and the Davenport DELTA model in a contextually sound, academic environment as taught by the likes of Wixom, Watson, Yeoh and Popovic. We avoid the trendiness of architecture, e.g. data fabric or mesh, and instead concentrate on the strategic, process-oriented, and organisational structures, which dictate value creation. The results show that business value is not a direct output of technological advancements. Instead, it is the outcome of a conscious, and coordinated development of human resources involved, governance processes, and analytical sophistication as a whole.

Index Terms— Business Intelligence, BI Frameworks, Augmented Analytics ML, NLP

I. INTRODUCTION

The modern business environment functions under the onslaught of information, which is created at an extraordinary pace and scale and makes the traditional method of analysis more and more obsolete. In this context, business intelligence (BI) legacy systems can hardly provide timely and relevant information. The main difficulty has appeared: “With the massive growth in data diversity, the traditional approach to BI has become less useful and requires additional work to obtain timely results” [1]. The manual data preparation, analysis and interpretation processes, which have historically been based on small groups of highly skilled data scientists and analysts, have placed an organisational bottleneck between data-rich and data-driven decision-making.

To meet this challenge, there has come in a new paradigm. The term augmented analytics was coined by the technology research company Gartner, that has defined it as a disruptive force. As per the analysis of the industry, “Research firm Gartner coined the term augmented analytics in its 2017 Hype Cycle for Emerging Technologies report and claimed it would be the 'future of data analytics'” [2]. This is a new application that transcends that of traditional BI in which dashboards remain static and the process of analytics requires manual expert queries, through artificial intelligence (AI) fundamentally embedded into the analytics workflow.

The formal definition given by Gartner gives an excellent outline of this paradigm. The firm defines augmented analytics as- “Augmented analytics is the use of enabling technologies such as machine learning and AI to assist with data preparation, insight generation and insight explanation to augment how people explore and analyze data in analytics and BI platforms”[3]. The main value statement being, AI should be used not to replace human analysis, but to complement and multiply human analysis, so that advanced analysis can be available to more people.

II. DESCRIPTIVE ANALYTICS

Analytical maturity is a process that begins with descriptive analytics. This phase is the base as it gives the empirical foundation on which any further value is anchored. Its main consideration is the hindsight and it uses historical data in order to create a true picture of the past. As defined in the literature, "Descriptive analytics is the interpretation of historical data to identify trends and patterns".[1]

In practicable business environment, descriptive analytics is the rear-view mirror of the organization. It provides the basic questions of "What happened? or, What is happening?".[2] In the case of a procurement department, this may include the answer to questions like "What did we spend on commodity X in the last quarter? and, Who are our biggest suppliers for commodity Y?".[2] The value generated here is generally underestimated whilst, without the capacity to describe the past right, an organization works in the dark. "Descriptive analytics summarizes what happened or is happening by pulling trends from raw data and providing insight into what these trends mean".[3]

The system used to provide this value is usually "business intelligence (BI) tools, data visualization and dashboards".[2] These tools can help the interested parties to see the reality making abstract rows of data understandable in the form of metrics. Although this phase has been criticised as reactive, it offers the required "insight into what these trends mean" [3], which is the single source of truth needed both to governance and compliance.

III. DIAGNOSTIC ANALYTICS

When an organisation is able to explain what has happened, the need then turns to the need to know why. This is the area of the diagnostic analytics. This stage generates business value by identifying the cause of performance variances thus allowing the management to recreate success or avert failure. “Diagnostic analytics can be used to identify the root cause of a problem”.[1]

The change in descriptive to diagnostic needs an enrichment of the analytical ability. It "requires more drilled-down and data mining abilities to answer, why did X happen?".[2] Considering an example, when descriptive analytics show that the sale of specific items has declined quarterly, diagnostic analytics will enable “sales leaders... to identify the behaviors of sellers who are on track to meet their quotas versus those who are not” [2].

Such techniques used in this stage are “data discovery, drill-down, data mining, and correlations” [4]. Organisations can transition to learning by drawing causal relationships. Diagnostic analytics “detects relationships between different variables through the analysis of historical data” [5], which allows the business to know the levers that can be used to achieve its performance. The value proposition in this case is minimisation of recurrence in the error of operations and maximisation of the efficient behaviours.

IV. PREDICTIVE ANALYTICS

The shift of the diagnostic to the predictive analytics is a significant turning point in the value chain. In this case, the organisation shifts the mode of reactive analysis to proactive strategy. This step "centers on taking that information and using it to forecast future outcomes".[1] "What will happen?".[6] is the main question answered here.

The value of business at this phase is based on the decrease of uncertainty and predicting market movements. "Predictive analytics typically deals with probabilities and can be used to predict a series of outcomes over time (that is, forecasting) or to highlight uncertainties related to multiple possible outcomes (that is, simulation)".[2] Using "predictive modeling, regression analysis, forecasting, multivariate statistics, pattern matching and machine learning (ML)" [2], organisations are able to optimise inventory levels, make financial performance predictions, and anticipate customer churn.

Nevertheless, the framework observes a weakness it informs us of what we should expect, but "does not, however, answer other questions, such as what should be done about it?".[2] The importance is in the warning or the opportunity detection, but not in the automated solution yet.

V. PRESCRIPTIVE ANALYTICS

The top of the Ascendancy Model is Prescriptive Analytics. This phase brings in the greatest business value and at the same time, necessitates the highest form of technical and organisational complexity. "Prescriptive analytics intends to calculate the best way to achieve or influence the outcome — it aims to drive action".[2]The element of this framework aims to find the answer to the question "How can we make it happen?".[6] It entails a combination of prediction models and optimization algorithms to suggest certain course of decision. "Prescriptive analytics includes both rule-based approaches (incorporating known knowledge in a structured manner) and optimization techniques... that look for optimal outcomes within constraints to generate executable plans of action".[2]As an example, a delay can be predicted using predictive analytics in a supply chain disruption. Prescriptive analytics, nevertheless, would consider millions of routing configurations and automatically suggest the alternative route that would maximise cost reduction and minimise delay. It "implements machine learning algorithms to make recommendations on further actions" [5], and thus successfully seals the loop between the information and its implementation of decisions.

Table 1 shows a comparative Analysis of Analytic Ascendancy Stages as discussed above.

Table 1: Comparative Analysis of Analytic Ascendancy Stages

Analytics Stage	Key Question	Primary Mechanism	Business Value Driver
Descriptive	"What happened?"	"Data visualization and dashboards" 2	Visibility and Operational Baselines
Diagnostic	"Why did it happen?"	"Drilled-down and data mining abilities" 2	Root Cause Analysis and Process Correction
Predictive	"What will happen?"	"Predictive modeling... and machine learning" 2	Uncertainty Reduction and Forecasting
Prescriptive	"What should be done?"	"Optimization techniques... [and] rule-based approaches" 2	Decision Automation and Outcome Optimization

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VI. DATA VISUALISATION TECHNIQUES

Drawing on the different types of analytics, descriptive, diagnostic, predictive, prescriptive, data visualisation converts these insights into a graphical format in the form of a chart, graph, map or an interactive dashboard. In the business intelligence field, it forms the main interface where the decision-makers process and take actions on insights.

Visualisation is significant since it allows treating the information faster and more accurately than reading the tables of numbers or technical analysis; patterns can be observed, tendencies can be more prominent, irregularities can be observed more easily, and interconnections between variables can be explained. It also helps overcome communication obstacles between the technical analysts and other non-technical stakeholders presenting the findings in a form easy to comprehend.

With more sophisticated BI environments, where the size of data processed and the combination of descriptive, diagnostic, predictive, and prescriptive analytics increase, visualisation is the most important mechanism that makes insights available, actionable, and incorporated into routine decision-making.

Practically, data visualisation is used throughout organisations in the processes of monitoring, exploration, explanation and prediction: and there are specific visual forms that are appropriate to particular analytic tasks:

Trend analysis: Line charts, area charts and time series plot are used to monitor performance over time and it shows seasonality, growth trend and long term trends.

Comparison: Bar charts and column charts allow easy comparison of categories performance of products, sales per region or departmental KPIs, and make the difference easily evident.

Diagnostics and Root-Cause Analysis: The heat maps, treemaps, scatter plot, and bubble charts can be used to reduce performance changes to anomalies, patterns, correlations, or clusters, which can be further investigated with greater rigour by examining the drivers of these changes.

Geospatial Understanding: Maps are applied when information about location is relevant e.g. in route optimisation, market expansion, or store performance by region, thus providing a spatial aspect to decision-making.

Operation and Executive Monitoring: Dashboards integrate various visual elements into one panel to allow real-time KPI tracking of both operational departments and executive performance briefing reports.

Predictive and Prescriptive Analytics: Forecast curves, comparisons of scenarios, and model outputs are displayed to make predictions and recommendations clear and understandable, therefore, helping managers to plan ahead.

Collectively, these strategies are used to explain how visualization can communicate insights, support exploration and lead to an actionable decision making process at both strategic, tactical and operational levels.

VII. APPROACHES TO BUILDING AND IMPLEMENTING BI FRAMEWORKS

The creation of business intelligence (BI) systems has undergone a radical change just the same way as paradigms of architecture. The traditional engineering process, the Waterfall model, has become more or less obsolete to Agile styles encouraged by the need to have faster time-to-value.

I. Waterfall Methodology

Waterfall model is a "linear approach" [30] that follows the same pattern as building the physical infrastructure. It is a structured approach which is a "rigid, highly structured approach that requires the execution of the project to be defined before any work can begin".[31]

The Linear Lifecycle

A Waterfall BI project is composed of a series of non-overlapping steps:

1. **Requirement Gathering:** "Project stakeholders define and document the system requirements".[32] The stage assumes that users can clearly define their exact requirements during the initiation.
2. **Design:** "System architects create a detailed design plan" [32], which often includes tedious data modelling.
3. **Implementation:** "The implementation phase involves coding or programming" [32], such as development of "complex means of ETL, cubes creation".[33]
4. **Testing:** "Thorough testing is conducted to ensure that all functionalities work as intended".[32]
5. **Deployment:** The system is finally made available to the users.

The Risk of Delayed Value

The inherent defect of Waterfall with regard to BI is that the requirements are the same. "Clients often don't fully know what they want at the front end, opening the door to requests for changes and new features later".[30] The business environment might be changed by the time the project is delivered which can be months or years later. "The outcomes of waterfall projects in terms of cost, timeline, and delayed benefits are commonly unfavorable".[34]

More importantly, this approach "virtually guarantees that business users won't get what they actually need" [35] since the requirements were frozen by the start. "Disappointed business users... only 'see' too late down the road the real impact of their -poorly expressed or interpreted- needs".[35]

II. Agile Business Intelligence

Agile BI uses the concepts of agile software development to data It is an "iterative approach that puts emphasis on testing and adapting".[36]

Core Principles and Scrum

Agile BI is built on "5 Key Principles":

1. **Continuous Planning and Delivery:** "Delivering small, incremental improvements on a continuous basis".[37]
2. **Team-Based Collaboration:** "Cross-functional teams working together to achieve a common goal".[37]
3. **Cycle-Driven Development:** "Create something that works, test it, and then improve it based on feedback".[37]
4. **Data-Driven Decision Making:** Making decisions with data to make the project.
5. **Always Improving:** Progressing with every iteration.

Majority of Agile BI teams use Scrum, a framework with "3 Team Roles: The scrum master, product owner, and developers and 5 Events: The sprint, sprint planning, daily scrum, sprint review, and sprint retrospective".[38]

User Stories and Sprints

Agile BI makes use of User Storeys as opposed to huge requirement documents. They are "simple, narrative descriptions of a feature or function that captures the end user's perspective";[37] such as: “As a sales manager, I would like to see the daily revenue by region so that I can resource the functions.”

Priorities on these storeys are a backlog that is delivered over Sprints- "short iterations, typically two to four weeks".[37] "The highest ranked user stories will be delivered within each new increment".[35] This makes sure that the most valuable features are built initially and early feedback can be given by the users.

Comparative Advantage

The change to Agile is justified by the statistics: "The agile method has a 15% higher rate of success than waterfall".[34] It reduces risk as "with each iteration comes new, actionable insights into what's working, what isn't, and what needs to change".[36] Whereas Waterfall uses "comprehensive documentation" [31] to manage risk, Agile relies on "continuous feedback".[31]

VIII. INFORMATION EVOLUTION MODEL (IEM)

Although the Analytic Ascendancy Model mainly deals with the methodological issues at play in the data analysis, the SAS Information Evolution Model (IEM) focuses on the organisational situation. This model asserts that the strategy of business value is not limited by the brilliance (algorithms) but by the maturity of organisational cultural, infrastructure and processes of information. The IEM describes a five-stage evolutionary path through which organisations pass in order to take the best out of their information assets.

Level 1: The Operational Enterprise

On the first maturity level, the organisation is working in the environment of data chaos, the level that is called Operate. This stage is typified by "Individualism and Day-to-Day Tactical Mode".[7] Such environment is ad-hoc in terms of data management, and "users take the first BI initiatives often with low support from senior executives".[8]

The business value realised at the point is minimal and highly localised. "Low benefits limited to small group of users; better access to data and static reporting".[8] Major friction is also witnessed, such as between SAS users as they all want to get their jobs priority and unreliable systems as "servers were crashing regularly".[9]]. As a result, the organisation keeps playing the game of reacting to urgent matters of operations but without utilising information in a strategic manner.

Level 2: The Consolidated Enterprise

Entities reach the stage of maturity and advance to the Consolidate level. Here, the focus is on "Consolidating Goals and Information into a Departmental View".[10] During this phase, organisations have been building regional data warehouses, and have been implementing "first interactive reporting tools".[8]

Value is based on standardisation of the metrics of the departments. "A certain business unit, a department or a member of senior management is responsible for IT management and creation of management dashboards".[11] Despite the lessening of redundancy with this consolidation, "silos" remain; marketing data might not blend with the finance data and this creates a dimensional tension where "the whole is less than the sum of the parts".[7]

Level 3: The Integrated Enterprise

The level of Integrate represents an enormous business value quantum leap. It is at this point that the business realises an "Integrated into an Enterprise-Wide View".[10] The distinguishing feature is that "coordination among people, processes, and technologies within the enterprise begins to take shape".[11]

At this stage, "information is perceived as a strategic asset".[11]], which makes possible the creation of a single source of truth- which is normally through a centralised data warehouse. This integration helps in cross-functional studies, including the evaluation of the effect of supply-chain delays on the level of customer satisfaction. "A senior executive, often from the business side, assumes the role of championing BI and analytics initiatives" [11], thus making sure that technical work is in line with corporate goals.

Level 4: The Optimized Enterprise

At the level of Optimise, the organisation uses its integrated data base to improve efficiency. It is "Optimized for Efficiency and Productivity".[10] The concentration is on improving the business engine. "Policies have evolved into principles and procedures that are well-documented, clearly communicated, and mostly automated".[12]

The framework argues that in this level, "creating high-quality, governed, and secured data is embedded into

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everyone's daily workflow processes".[12] This shift brings the organisation to the next level of having data possession to having trustworthy, governing data, thus reducing the amount of time wasted during the debate on numerical validity and maximising the time spent on strategic decision making. "The enterprise extends its performance metrics framework to include partners and customers, emphasizing business value over internal processes".[11]

Level 5: The Innovative Enterprise

The last level is the Innovate stage which is the last level and is "Driven by Continuous Innovation".[10] In this case, analytics can be a cause of disruption, allowing one to develop "new products and business models — Developing new services, pricing models or propositions using predictive insights".[13]

An organisation with an “Innovate” level is able to maximise the processes which are already established and also ask questions which used to be taboo. "Information is perceived as a strategic asset, and BI and analytics are leveraged to drive revenue... or deliver exceptional customer service".[11] According to the model, the organisation at this maturity stage acts as an "Analytical Competitor," utilizing "proprietary, algorithmically-driven software" to dominate markets, much like "Netflix is a company built on an algorithm".[14]

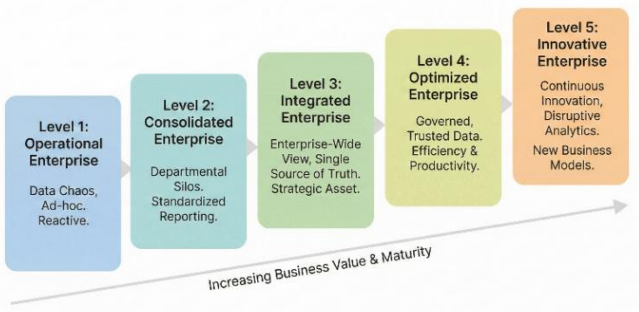

Figure 1: The IEM Model Levels

IX. DELTA PLUS FRAMEWORK

Developed by the International Institute of Analytics (IIA), and Thomas Davenport, DELTA Plus model provides a component-based model of deriving business value. Unlike sequential stages of Ascendancy or IEM models, DELTA focuses on the seven key factors that should exist and be aligned to be successful: Data, Enterprise, Leadership, Targets, Analysts, Technology, and Analytical Techniques.

I. Data: The Raw Material of Value

The framework claims that "accessible, high quality data is the non-negotiable prerequisite for value.”[15] "The foundation of any analytics initiative is high-quality, accessible, and integrated data".[16] This aspect highlights the need of breadth and integration.

In the absence of this, it is impossible to conduct advanced analytics. "Data is integrated in a data warehouse or data lake" [17] to enable the evolution of the localised analytics to enterprise-wide analytics. The framework underlines that "high performers (in terms of profit) were 50 percent more likely to use analytics strategically" [5]. The basis of this correlation lies with data quality.

II. Enterprise: The Strategic Scope

The Enterprise component implies that analytics should be handled in a comprehensive manner. "An enterprise approach is accomplished by setting an analytics strategy and building a road map for strategy implementation".[18] This minimises the inefficiency of resources.

The value is created when "resources [are] built effectively and deployed strategically without duplication of effort".[18] Enterprise perspective enables organisations to discover cross-functional synergies including the use of customer integration strategies to "create value for both sides -suppliers and buyers".[19]

III. Leadership: The Cultural Driver

The most outstanding distinguishing feature of the DELTA model is perhaps the Leadership. The model demands "Leadership – Encourage the emergence of analytical leaders in functions and business units".[18]

"Strong data leadership... [from] the CEO and chief data officer sends a powerful message".[20] Leadership that is effective is characterised by "passion and commitment" [14] to evidence-based decision-making. "Traits of analytics-savvy leaders include promoting data literacy, encouraging experimentation, and setting clear performance expectations".[16] Devoid of this higher-level drive, analytics projects tend to stagnate in the IT department, without providing a business value.

IV. Targets: Focusing on Value

The Targets component responds to the following query: Where analytics is to be applied? The framework suggests to “target low hanging fruit"[18] first to create value, and then grow. "Analytics initiatives are focused on key high value, high impact business areas".[17]

Capital One is the example of successful organisations that use this strategy, focusing on particular high-value decisions. "Capital One's analytics initiative... has spurred at least 20% growth in earnings per share every year since the company went public".[21] By targeting "actuarial data to price our premiums accurately, organizations can avoid pricing mistakes".[14]

V. Analysts: The Human Capital

"An analytical organization needs a cadre of highly skilled professional analysts and data scientists".[18] The DELTA model distinguishes between the Analytical Professionals who can create algorithms, Analytical Semi-Professionals who can use visual and simple statistical tools and Analytical

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Amateurs who can use spreadsheets.

The value derivation requires a balanced set of these abilities. "Identifying pockets of analysts and skills and offering analytical skills training" [18] guarantees that the company will have the human power to analyse what the technology will provide.

VI. Tools and Techniques

The "Plus" in DELTA Plus refers to the incorporation of the words Technology and Analytical Techniques. This is in recognition of the fact that as much as culture is most important, modern analytics needs powerful tools. "Technology – Adopt predictive analytics tools and encourage their use".[18]

This consists of deploying "machine learning (ML) algorithms and "cloud-based data warehouses".[17] The value comes out of the ability to perform complex "Analytical Techniques" like, "optimization, web analytics, and other special purpose techniques"[18] which were previously computationally infeasible.

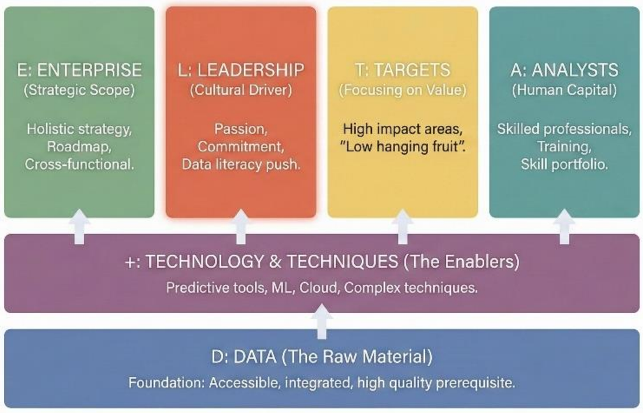

Figure 2: DELTA Plus framework

Table 2 shows the DELTA Plus Elements and Value Contribution towards Business Analytics and Business Value.

Table 2: DELTA Plus Elements and Value Contribution

DELTA Element	Focus Area	Business Value Contribution
Data	Quality and Accessibility	"The foundation of any analytics initiative" 16
Enterprise	Strategy and Roadmap	Prevents duplication; aligns resources 18
Leadership	Passion and Commitment	"Sends a powerful message" of data prioritization 20
Targets	High-Impact Areas	Focuses efforts on "key high value... business areas" 17
Analysts	Skills and Roles	Ensures human capacity to interpret and act on data 18
Technology	Tools and Infrastructure	Enables advanced "predictive analytics tools" usage 18
Techniques	Algorithms and Methods	facilitating "optimization... and special purpose techniques" 18

X. BI VALUE CHAIN

BI Value Chain framework offers process-oriented perspective of value-creation process of data. It splits the lifecycle of information into its various phases, each of which adds some value to the original information.

I. Data Sourcing and Engineering

Value chain starts with Data sourcing which is defined as "accessing the data" from the myriad internal and external sources available to the enterprise.[22] This is then closely succeeded by Data engineering and analysis where the raw material is then refined. "After data sourcing, the next logical step is information engineering and analysis".[22]

At this point value is generated through purification. "Ensuring data completeness by eliminating gaps in records" and "validating data relevance to business objectives" [23] preventing the garbage in, garbage out phenomenon. At this step, there is also "Data Cleaning & Deduplication – Removing inconsistencies, correcting errors, handling missing values".[23]

II. The Role of Data Warehousing

The Data Warehouse is the hub of the value chain. "A data warehouse acts as the backbone of business intelligence by providing the structured, reliable data needed for analysis".[24] The repository makes possible the single source of truth.

"Without a warehouse, BI will struggle to perform".[25] The warehouse combines data of the "CRM systems, customer interactions, IoT, social media" [23], converting disorganised inputs into an integrated property. Such consolidation "serves as your organization's centralized repository, integrating data... into a single, consistent, historical record".[26]. The obtained value is "Dramatically Faster Decision-Making" and "Improved Data Quality and Consistency" [26], as the stakeholders cease to argue about the validity of data and concentrate on its implications.

III. Analysis and Decision Support

After sourcing and warehousing data, the chain of values moves to "Situation awareness, Decision-making, and Decision support".[22] This is the layer of translation between IT and business. "Business Intelligence (BI) is a type of architecture that supports collecting and analyzing data to come up with meaningful information about the business".[22]

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Additional value is added by decision support by "identifying the risks, opportunities, benefits, profit, pitfalls, cost-to-benefit ratio... and estimating the business value of the proposed decisions".[22] This step converts abstract data to actual business alternatives.

IV. Evaluation and Iteration

The last, and least considered phase is "Evaluation and iteration".[22] This is a feedback loop that is vital in continuous improvement. "This stage deals with answering the question—'what is happening right now?' as this deals with keeping an eye on the business's day-to-day activities".[22]

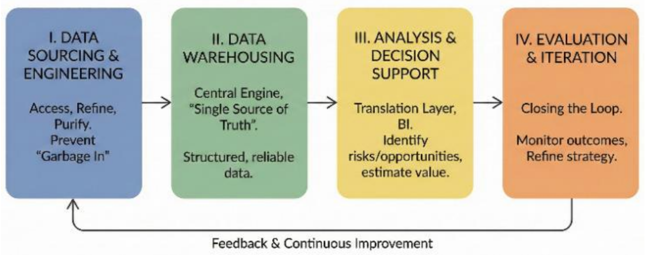

Figure 3: The BI Value-Chain Framework

By analyzing the outcomes, the organizations may further refine the models responsible fpr data sourcing and analysis tasks. "Monitoring and analyzing these paths helps you gain information about how users engage with your product" [27], enabling for an iterative refinement of the business strategy.

XI. CRITICAL SUCCESS FACTORS (CSF) FRAMEWORKS

Whereas maturity models define the parameters of success, Critical Success Factor (CSF) frameworks explain the processes that need to be in place to achieve it. Such frameworks determine the key elements that need to be in place so that a BI initiative can produce business value.

I. Wixom and Watson's 4-Tier Model

Wixom and Watson (2001) came up with an iconic framework, which separates technical success and organisational success. Their model is developed based on a hierarchical structure of success factors:

- **Infrastructure Factors:** They determined that "data quality and senior management support are considered the most important CSF".[28]
- **Implementation Factors:** They are "Management Support, Resources, User Participation, and Team Skills".[29]
- **Technical Implementation Success:** This level addresses the areas of "Source Systems," "Development Technology," and "Data Quality".[29]
- **Organizational Implementation Success:** The final objective is determined by "Perceived Net Benefits" and "User Satisfaction".[29]

One of the key observations that have been brought out by their framework is that "information quality and system quality constructs cannot be conceptualized as latent exogenous variables... Rather, they are to be understood as latent endogenous variables".[29] Therefore, quality data and systems are not input but outputs of a good project management and support within an organisation.

II. Yeoh and Popovic's Integrated CSF Framework

Yeoh and Popovic further developed this by classifying CSFs into three dimensions namely Organisation, Process, and Technology.

- **Organizational Dimension:** This is the most important dimension. "Organizational factors play the most crucial role in determining the success of a BI system implementation".[30] It includes "committed management support and sponsorship" and clear business vision".[30] "Hence, BI stakeholders should prioritize on the organizational dimension ahead of other factors".[30]
- **Process Dimension:** This dimension pays attention to the methodology of execution and comprises of "business-centric championship and balanced team composition" and a "business-driven and iterative development methodology".[30]
- **Technological Dimension:** This dimension is vital but in most cases it takes the second position to the other two. It needs a "business-driven, scalable and flexible technical framework" and "sustainable data quality and integrity".[30]

The model underlines that there is no use of technology only. "Implementing BI is not just a simple task of buying a set of software and hardware; it requires proper infrastructure and resources over time".[28] Table 3 represents the CSF dimensions of Yeoh and Popovic in a tabular format.

Table 3: Yeoh and Popovic's CSF Dimensions

Dimension	Critical Success Factors	Strategic Implication
Organizational	"Committed management support and sponsorship" 30	Prioritize executive buy-in above technical specs.
Process	"Business-centric championship" 30	Ensure the project is led by business needs, not IT.
Technology	"Scalable and flexible technical framework" 30	Build infrastructure that can evolve with business needs.

XII. GOVERNANCE, CULTURE, AND LEADERSHIP FRAMEWORKS

Soft elements of BI, governance, culture, and leadership are also becoming acknowledged as the most difficult parts of the value equation. The frameworks in this area focus on establishing a climate that will ensure analytics.

I. Gartner's Data Governance Maturity Model

Governance is characterised as the mechanism of decision rights and accountabilities of processes that are related to information. The model created by Gartner is the continuation of the chaos to control in that it is developed to move through the stages of Aware to Optimised.

- **Level 1 (Aware):** Organizations "know what their issues and challenges are" but lack the structure to fix them.[12] "The result is typically a low level of data quality and data trust".[12]
- **Level 2 (Reactive):** Governance is event driven. Organizations "respond to 'fire drills' (such as a data breach...)".[12] This methodology "can still result in lost revenue and lost customer confidence".[12]
- **Level 3 (Proactive):** "A proactive company has tasked information owners and data stewards with maintaining and monitoring data quality".[12]
- **Level 4 (Managed):** Governance is systemic. "Policies have evolved into principles and procedures that are well-documented... and mostly automated".[12]
- **Level 5 (Optimized):** Governance is not visible. "Creating high-quality, governed, and secured data is embedded into everyone's daily workflow processes".[12]

Value is created through building trust. "In order for you to use this consistent trustworthy information in your tools of choice, we have opened up the Looker modeling layer... to ensure the information... doesn't stay there".[31]

II. McKinsey and HBR Data Culture Frameworks

The way of practical use of data is defined by culture. "Data culture is the collective behaviors, beliefs, and practices within an organization that emphasize transparency, collaboration, and integration".[32]

The pillars presented in McKinsey structure are "Leadership and sponsorship, Governance policies and procedures, and Data stewards".[33]

HBR presents a strategic dilemma: Data Defence / Data Offence

- **Data Defense:** Is "about minimizing downside risk".[34] It encompasses compliance, fraud prevention and security.
- **Data Offense:** "Focuses on supporting business objectives" such as revenue generation and customer acquisition.[34]

The model suggests that value is created when there is a balance of these two dimensions. "The strategy enables superior data management and analytics—essential capabilities that support managerial decision making and ultimately enhance financial performance".[34] There should be a robust data culture which calls on a "flexible data and information architectures that permit both single and multiple versions of the truth" [34] to meet defensive and offensive requirements.

III. Leadership Maturity in Analytics

Culture is the catalyst of leadership. The "Leadership Maturity Model" [35] provides the development of leaders into an Emerging to a Visionary one.

- **Functional Leaders:** "Focus on optimizing processes and achieving specific outcomes".[35]
- **Strategic Leaders:** "Possess a strong vision for the future and align their teams toward achieving organizational goals".[35]
- **Visionary Leaders:** "Shape the direction of their organizations... and leverage their insights to drive innovation".[35]

In the sense of the BI context, "Leadership... implies the development of capabilities that respond to high demands".[36] "Strong data leadership. Support from the CEO and chief data officer sends a powerful message" [20].

XIII. CONCLUSION

The topography of business value derivation frameworks of Business Intelligence and Analytics is varied and diverse. There is no one single framework that can be used to describe the full complexity of the challenge but instead they are used as complementary lenses with the help of which organisations can look at their journey.

The Gartner Analytic Ascendancy Model outlines the path to be taken between descriptive hindsight and prescriptive optimisation. It shows that there is value proportional to complexity.

SAS Information Evolution Model and the DELTA Plus by Davenport offer the who and where element, which emphasises maturity and structural aspects of an organisation that need to be in place to facilitate such a direction. They show that technology without a well-established organisation is wasted.

The BI Value Chain and CSF Frameworks explain the how- how the actual processes and the critical elements that should be handled in order to transform raw data into decision support. They depict that the process itself is weak and needs strict rule.

The BI Value Chain and CSF Frameworks explain the how- how the actual processes and the critical elements that should be handled in order to transform raw data into decision support. They depict that the process itself is weak and needs strict rule.

Lastly, the Cultural and Governance Frameworks why, which is the alignment of analytics with business strategy by the use of Data Offence, and trust by Data Defence.

To sum up, business value of BI is not an entirely technological implementation undertaking but a project of organisational transformation. The stringent implementation

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of these frameworks is what transforms that definition to a sustainable competitive advantage, as research proves, "Business analytics is the use of math and statistics to collect, analyze, and interpret data to make better business decisions" [1]. Those organisations which manage to move through these structures of "Analytically Impaired to Analytical Competitor" [14] do not just observe their data; they envisage their future.

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