Integrating Business and Process Analytics for Enhanced Data-Driven Decision-Making

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Abstract

By integrating Business Analytics and Process Analytics, organizations can gain a deeper understanding of the relationship between process inefficiencies and business outcomes, leading to improved data-driven decision-making. This integration, however, is often overlooked, with limited methodological guidance for systematically combining these two analytical domains. Motivated by this challenge, this paper proposes a methodological approach for the identification of analytical visualizations that allow the aforementioned integration to be achieved systematically. The proposed approach is tested in a running example, which includes an instantiation of a Data Warehouse system for supporting data integration and analysis for business process analytics.

Keywords

Analytical Requirements, Business Process, Performance Indicators, Process Analytics

1. Introduction

The large amount of data available in organizations has catalyzed the development of advanced analytical techniques to extract valuable insights [1]. Business Analytics (BA) has emerged as a cornerstone for understanding past performance and predicting future trends. However, focusing solely on business indicators can be a limited approach, as it fails to consider the impact that the underlying processes have on such indicators.

Process Analytics (PA) offers a complementary perspective by delving into the sequence of activities that constitute business operations. Techniques such as process mining [2] provide valuable insights into the execution of processes, identifying bottlenecks, and uncovering inefficiencies. However, while these methods excel at understanding the internal mechanics of processes, they do not offer an integrated process- and business-centric analysis to gain a holistic view of organizational performance [3].

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BA and PA have traditionally been pursued as separate domains. While data warehouses integrate data that allows the analysis of relevant historical data for business insights, process mining tools have focused on extracting process models from event logs. Such a siloed approach can hinder a comprehensive understanding of organizational performance. As stated by [4], Process Science, which includes PA, requires contributions from various disciplines, offering perspectives such as human, social, environmental, economic, and technological (including Data Science, which encompasses BA). By integrating these diverse perspectives, process science can provide a more comprehensive view of processes and their impact on businesses. Thus, to unlock the full potential of data-driven decision-making, a more integrated approach is needed.

This paper proposes a methodology for the integration of PA and BA. We outline a conceptual approach for identifying relevant indicators for the business and operational processes and determining the types of visualizations to use in their analysis. With this approach, we aim to empower decision-makers with a comprehensive perspective on organizational performance through the integration of performance indicators and effective visualization techniques.

This paper is structured as follows. Section 2 summarizes the related work. Section 3 presents the proposed methodological approach and delves into the running example. Section 4 evaluates and discusses the approach. Section 5 concludes with the main findings and future work.

2. Related Work

Organizations are increasingly recognizing the importance of metrics-driven management in achieving their strategic goals, reflecting a broader trend toward data-driven decision-making and performance optimization. While the academic and practical significance of these metrics has long been acknowledged, as evidenced by studies such as [5], their role is now being viewed through a new lens, emphasizing their critical importance in contemporary business environments. As organizations navigate an increasingly complex landscape, the ability to harness and interpret vast amounts of information has become crucial for maintaining a competitive advantage and achieving strategic ambitions. [6] and [7] further state that *"the synergy between business performance metrics and process efficiency indicators has the potential to provide a comprehensive understanding of organizational dynamics"*.

In 2010, [5] introduced a framework integrating Business Process (BP) and Information Technology (IT) management with Business Intelligence (BI) at all decision-making levels (strategic, tactical, and operational). This framework enables real-time monitoring and analysis to optimize operations and align business activities with strategic goals. It connects business process data with operational activities, implements business rules and Key Performance Indicators (KPIs), and generates automatic alerts to prevent issues. Despite limitations, such as the absence of practical use cases, insufficient technical detail, and a theoretical focus, the study emphasises a more comprehensive approach to business performance management.

Research in subsequent years has refined this integration, focusing more on practical applications. For example, [8] proposes a process-oriented approach using the Business Process Model and Notation (BPMN) to integrate interrelated business processes into an analytical data model, encompassing behavioral aspects and performance measures. This approach results in a comprehensive analytical data model aligned with both strategic goals and operational execution. However, the study does not fully address the integration of detailed operational data or practical implementation challenges. Similarly, [9] advances this discussion by presenting a Data Warehouse (DW) model specifically for analyzing business process data. This study uses BPMN 2.0 to emphasize the symbiotic relationships between business process management and business intelligence, proposing an analytical data model for DW systems. While this study emphasizes the relationship between business process management and BI, it lacks a detailed integration of operational data with business performance indicators.

By 2020, the focus shifted toward integrating business and process data within complex technological environments. [10] explored this integration by identifying various intra- and inter-organizational collaborative process scenarios and proposed an integrated meta-model to address data matching and integration challenges. This model-driven approach provides a unified view that captures all data consistently, facilitating process extraction and data mining techniques, but may fall short in providing a detailed framework for practical implementation within specific organizational contexts.

More recently, [11] proposed the Business and Process Analytics Data Warehouse Meta-Model (B&PADWM), which integrates the traditional business perspective in a DW system with the process perspective. This meta-model details the activities supporting business processes, enabling an analysis of both business operations' efficiency and the effectiveness of supporting processes. By highlighting the cause-and-effect relationships between these dimensions, this approach helps organizations assess operational efficiency and process effectiveness. The B&PADWM meta-model supports strategic decision-making based on a comprehensive understanding of operational knowledge.

Building on the work of [11], this paper proposes a methodology to bridge the existing gaps. This methodology provides a structured approach to integrating business performance indicators with operational data by defining analytical requirements, proposing a multidimensional Data Warehouse model, and generating visualizations for decision-making. This approach aims to enhance organizational efficiency and effectiveness by addressing the limitations of previous studies, including the need for a comprehensive and actionable data analysis approach that integrates both business and operational perspectives effectively.

3. Integrating Business and Process Analytics

The integrated analysis of business and process data requires a methodological approach to guide and support the identification of a data model that integrates these two perspectives highlighting how they impact each other. Improving organizational efficiency and efficacy requires analyzing the data associated with the business processes and, also, data associated with the operational processes that include the activities performed by the several actors enrolled in the business processes. As can be seen in Figure 1, this work considers that Business Process Analytics includes the business processes and their indicators to unveil how the business is performing. These business processes produce/generate data that needs to be processed to highlight useful information about the business indicators. Decision-makers use this information to devise strategies and actions that impact business performance intending to improve it. Besides the data from the business processes, vast amounts of data are collected from the supporting operational

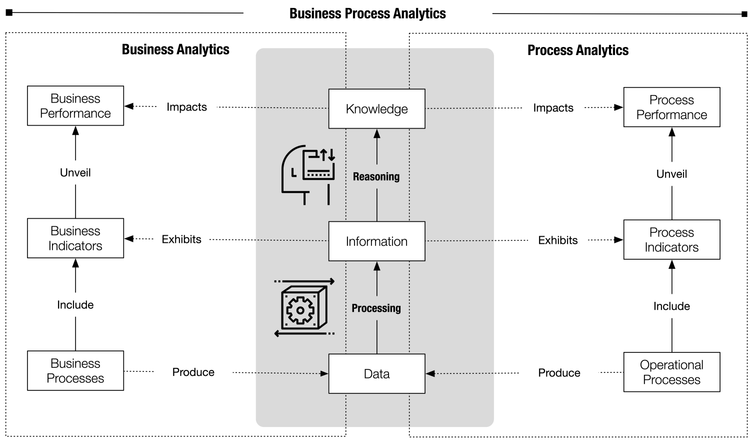

Figure 1: Business Process Analytics.

processes requiring concerns about PA. In this paper, Business Process Analytics considers the analysis of business indicators (the BA perspective) and operational indicators (the PA perspective) and intends to highlight how business and operational processes impact each other.

3.1. Proposed Methodological Approach

The proposed methodological approach considers that to properly establish analytics that relates process and business data, there is the need to identify the associated analytical requirements. These will integrate business and operational concerns in improving efficiency and efficacy. Figure 2 details the methodological approach that contributes to the field by systematically transforming raw process data into insights through a series of well-defined steps. After collecting the data or having access to it, including event logs, transaction records, or any other type of process-related information, the steps that follow are:

1. **Process Model.** This step requires a representation of the process model using, for instance, Process Mining techniques as they allow for the extraction of a process model from the event logs. This model visually represents the flow of activities, the objects, the sequence of events, and the interactions between different entities within the process. These activities and related events can be modeled following the OCEL 2.0 standard, Object-Centric Process Mining [12], as this facilitates the identification of patterns, dependencies, and inefficiencies in the operational processes. [13]. In OCEL 2.0, objects refer to the different activities and their events.
2. **Conceptual Data Model.** This step involves identifying the key concepts (entities or classes), relationships, and data attributes that are central to the process. By analyzing the process model, it is possible to identify the types of activities carried out by the objects involved and how these activities relate to the underlying data structures, providing a high-level abstraction of the data.
3. **Analytical Requirements.** This step is related to the identification of the Analytical Requirements to be fulfilled considering the background knowledge provided by the

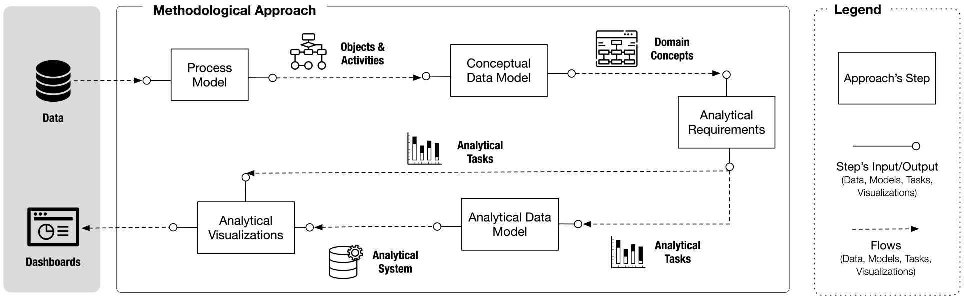

Figure 2: Proposed Methodological Approach.

process and conceptual data models. This involves determining the analytical tasks needed to support decision-making. It is a crucial step as it ensures that the analytical model and supporting visualizations are aligned with the strategic goals of the organization.

4. **Analytical Data Model.** In this step, an Analytical Data Model is identified to support the analytical requirements. It organizes the data in a way that facilitates efficient querying and reporting, often involving data warehouses, data marts, or other data systems.
5. **Analytical Visualizations.** This step involves developing visualizations based on the analytical requirements and the supporting analytical data model. These transform possible vast amounts of complex data into intuitive insights, using tools such as dashboards.

3.2. Running Example

For detailing the methodology, the running example outlines the management of customer orders [14] (Figure 3), covering the registration, payment, packing, and shipping of orders. Staff from sales, warehousing, and shipment departments are involved. Customers place orders which are assigned to a dedicated sales representative for registration and payment processing. Warehousing staff check stock, reorder if necessary, and prepare items for shipment. Packages are compiled and shipped, often with some policy deviations in loading assistance, and deliveries may fail repeatedly before success. In the orders, each product has a price that increases with time due to inflation negatively impacting customers' orders. After placing an order (*place order*), sales employees register the order (*confirm order*) and handle the payment processing (*payment reminder*, *pay order*). For preparing the orders, a warehousing employee verifies the availability of the ordered items and, when necessary (*item out of stock*), reorder items of products (*reorder item*) to have availability of items to pick (*pick item*). Packages are prepared (*create package*) for customers including the items available for shipment (*send package*) and additional packages may be sent for items of the same or different orders. As deliveries may fail (*failed delivery*), packages are resent until successfully delivery (*package delivered*).

3.3. From Data to Visualizations

Following the proposed approach, the Process Model (already available as shown in subsection 3.2) supports the identification of a Conceptual Data Model that includes the concepts (objects in

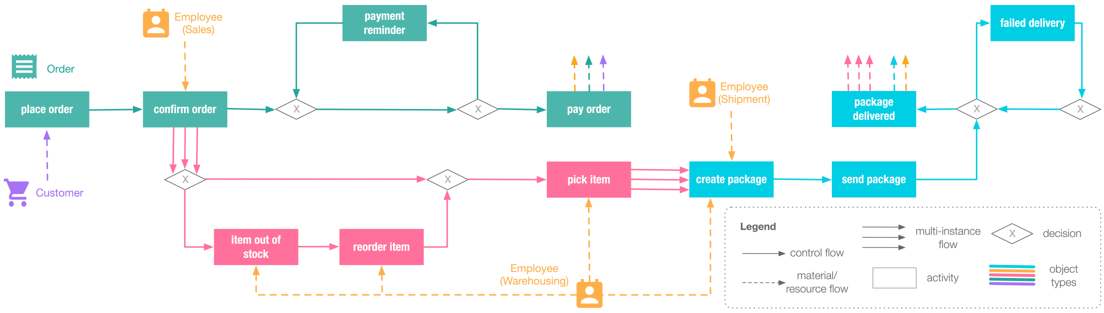

Figure 3: Process Model: Management of Customer Orders. Adapted from: [14].

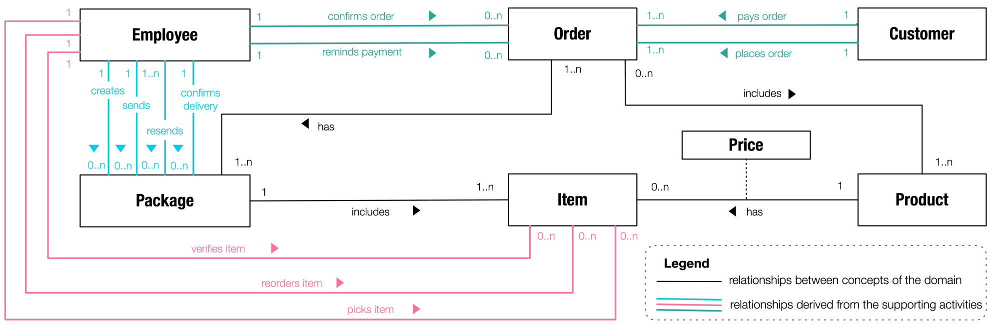

Figure 4: Conceptual Data Model. Extended from: [11].

OCEL 2.0) of the domain addressed in the operational processes and the relationships between those concepts gathering the information that flows in the control or material/resource flows. If no Process Model exists for a given data set, it has to be designed using techniques such as process discovery. The Process Model depicted in Figure 3 includes six objects: *Order*, *Customer*, *Employee*, *Package*, *Item*, and *Product*. When the behavior of the Process Model, regarding its activities, is represented as relationships, Figure 4 depicts the obtained Class Diagram. This model is abstracted and represented using an approximation of the Unified Modelling Language (UML) Class Diagram notation. The representation of the classes has been simplified using a square to represent the main concepts and no attributes have been specified to improve the readability of the model. In this model, an extended version from [11], two types of relationships are considered: those that result from the activities of the supporting operational processes and the way they were defined and articulated, and those relationships that relate common concepts of the domain. Additionally, this model makes explicit an association class between *Item* and *Product*, as the data contains the evolution of prices over time.

With the Conceptual Data Model and to identify the Analytical Data Model, it is essential to define the Analytical Requirements. These will guide the identification of the logical model of the data system to be implemented. In this running example, it is considered the implementation of a DW system, justifying an Analytical Data Model represented by a multidimensional model with fact tables, their level of detail, their dimension tables, and their relationships. The

Analytical Requirements must consider the business processes addressed in the Conceptual Data Model, namely **Manage Orders**, **Manage Packages**, and **Manage Prices**, and the operational processes that support the daily operation of the organization (activities and their events). To effectively integrate the business and the operational processes, the key question to be addressed is *which analytical requirements should be considered?*. This paper highlights the use of i* as this allows the specification of Strategic, Decision, and Information Goals [15] when implementing a DW system. Analytical requirements cannot focus exclusively on Strategic Goals (SGs) for the business processes, but must take into account that SGs might be supported by Decision Goals (DGs) with business and operational concerns. Consequently, the Information Goals (IGs) will focus on the integrated analysis of business indicators and operational indicators.

As an example, consider an SG associated with **Orders**, such as *Decrease Processing Costs*. To achieve this goal, with this integrated perspective between the business and supporting activities, DGs can address decreasing the number of packages, the processing time, and the shipping time. While from the business perspective decreasing the number of packages will decrease costs, from the operational perspective it requires more efficient activities in confirming orders (as this will speed up the warehousing and shipping operational processes), creating packages, and picking items, among others. As shown in Figure 5, the defined DGs are supported by several IGs. For each IG, the ReqViz framework [16] is used to obtain the most suitable analytical visualizations that will support the decision-making process. To achieve this, we complete the requirements model (Figure 5) with the visualization context (represented in yellow for IG 17). This context includes the goals that the data visualization aims to reflect (VG), the type of interaction that users will need to have with the visualization (IT), and the elements from the DW that will populate the visualization. These are represented in categories (Cat) and measures (M). It should be noted that both the VGs and the ITs are chosen from a predefined list by following the guidelines presented in [16].

With the identified analytical requirements (Figure 5) is now possible to derive the Analytical Data Model for the DW system. Although the proposed approach is now specifically used for this data system, its use is not mandatory. Different data systems can be used, as long as their modeling principles are followed. In a DW, we need to consider the inclusion of fact tables and dimension tables [17]. The fact tables address the business processes at different levels of detail. As previously mentioned, in the Conceptual Data Model we identified **Manage Orders**, **Manage Packages**, and **Manage Prices**, but from the operational perspective, the **Manage Activities** process needs to be considered, facilitating the analysis of highly detailed data about the activities and events of the business processes. Considering the analytical requirements and the need to derive a multidimensional model for the supporting DW, Figure 6 shows how the different IGs, the objects included in the process model and the timestamp object implicit in the events, can support the identification of the required fact tables and their indicators. Also, this mapping of the specified IGs and objects also supports the association of the dimension tables to the identified fact tables. As shown in Figure 6, for each IG, there is the need to identify the indicator/measure to be considered, how it is computed in case it needs to be derived, and the aggregation function that should be used for analysing the data.

The formalization of the Analytical Data Model considers the knowledge explicit in Figure 5 and the detail of the Conceptual Data Model, Figure 4, as the granularity of the fact tables may impose different relationships between the fact and dimension tables or different indicators.

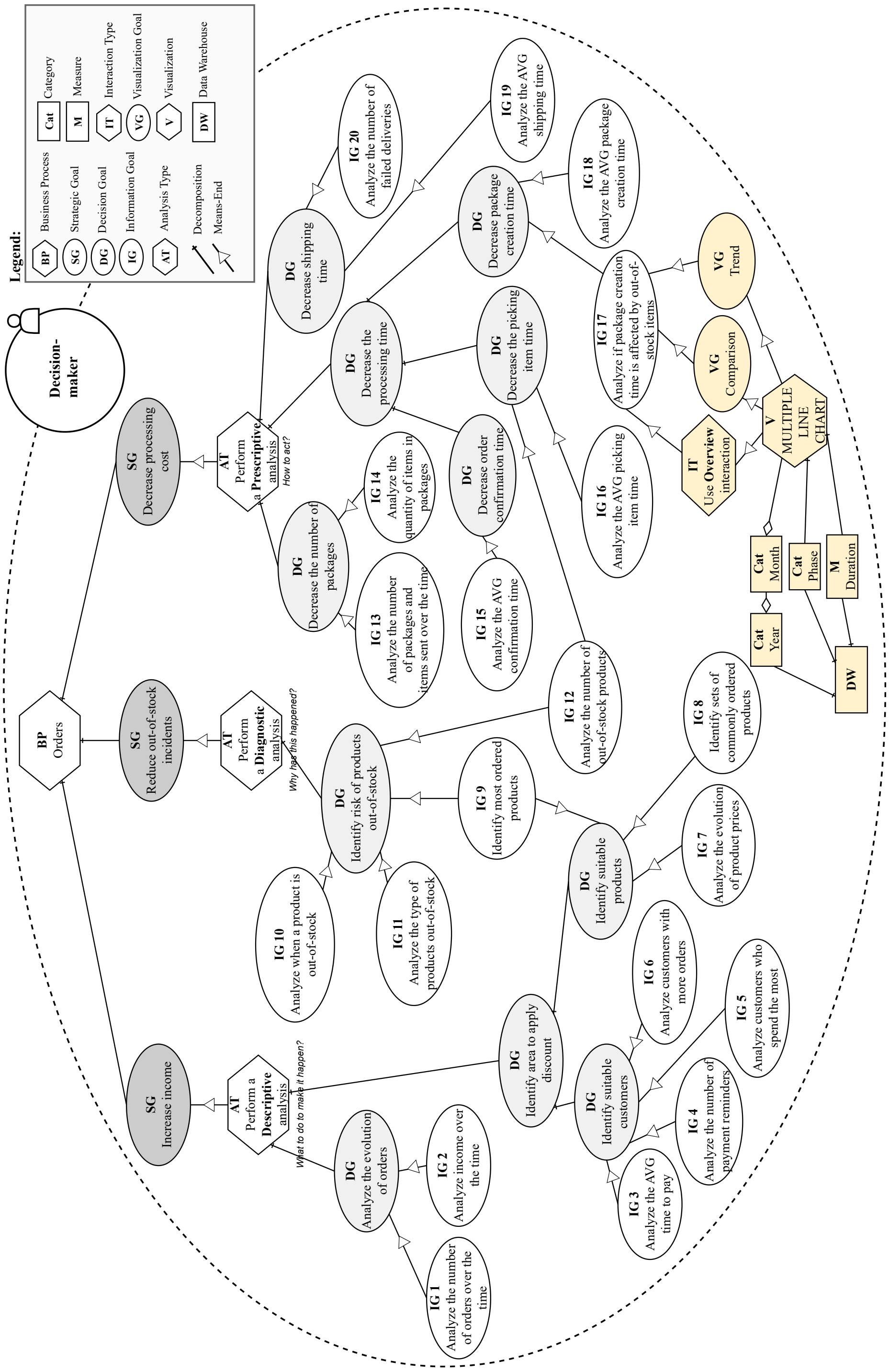

Figure 5: Analytical Requirements for Orders.

For instance, as can be seen in Figure 7, as the **Orders** fact table includes one record per order, there is the need to include global indicators of the orders, such as the number of reminders sent, the number of days the customer took to pay, or the number of days to confirm the order.

Now that we have analytical tasks and the supporting DW, the visualizations that will support the decision-making process can be developed. As [16] states, the type of analysis (AT) element (Figure 5) determines the visualizations grouped within the same dashboard. Consequently, these analytical requirements indicate that 3 dashboards are required. However, due to space constraints, we will focus on the dashboard developed for the SG *Decrease processing cost*.

Having the visualization context for each IG defined (yellow part of Figure 5) we can identify the most suitable visualization type that will compose the dashboard. In this running example, we exemplify visualization context and suitability scores for IG 17. To determine the best visualization type for achieving IG 17, authors in [18] establish a classification system based on 7 coordinates which are represented in Table 1. First, the (1) User is classified as *Tech* because the decision-maker has skills in data visualization. If the user had trouble understanding complex data visualizations, it would have been classified as *Lay*. Next, the (2) VG and (3) IT come from the Analytical Requirements (Figure 5). The VGs have been defined as *Comparison*, as the purpose is to compare values, and as *Trend*, so that similarities and dissimilarities can be identified. The IT has been defined as *Overview* to provide an overview of the entire data collection. Then, the (4) Dimensionality is stabilized as *n-dim* since there are more than two variables to visualize, and (5) Cardinality as *Low* since data contains few items to represent. Finally, the (6) Independent type (referring to Month and Phase) is defined as *Nominal* as it is

	Timestamp	Customer	Order	Product	Item	Package	Employee	Process (Manage ...)	Fact Table	Indicator	Aggregation Function
IG 1	x		x					Orders	Orders	Order Count	SUM/COUNT
IG 2	x		x					Orders	Orders	Order Value	SUM
IG 3	x	x	x					Orders	Orders	Days to Payment [Pay Order Date - Confirm Order Date]	AVG
IG 4	x	x	x					Orders	Orders	Number of Reminders	SUM
IG 5	x	x	x					Orders	Orders	Order Value	SUM
IG 6	x	x	x					Orders	Orders	Order Count	SUM/COUNT
IG 7	x	x	x	x	x			Orders	Orders Detail	Item Price	AVG
	x			x	x			Prices	Prices	Item Price	AVG
IG 8	x	x	x	x	x			Orders	Orders Detail	Item Count	SUM/COUNT
IG 9	x	x	x	x	x			Orders	Orders Detail	Item Count	SUM/COUNT
IG 10	x		x	x	x			Activities	Out of Stock	Item Count	SUM/COUNT
IG 11	x		x	x	x			Activities	Out of Stock	Item Count	SUM/COUNT
IG 12	x		x	x	x			Activities	Out of Stock	Item Count	SUM/COUNT
IG 13	x					x		Packages	Packages	Package Count	SUM/COUNT
	x			x	x	x		Packages	Packages Detail	Item Count	SUM/COUNT
IG 14	x			x	x	x		Packages	Packages Detail	Item Count	SUM/COUNT
IG 15	x		x					Orders	Orders	Days to Confirm [Confirm Order Date - Place Order Date]	AVG
IG 16	x			x	x	x	x	Packages	Packages Detail	Days to Pick [Pick Item Date - Confirm Order Date]	AVG
IG 17	x		x	x	x			Activities	Out of Stock	Days Out of Stock [Pick Item Date - Out of Stock Date]	AVG
IG 18	x					x		Packages	Packages	Days to Create [Create Package Date - (first) Pick Item Date]	AVG
IG 19	x					x		Packages	Packages	Days to Ship [Send Package Date - Create Package Date]	AVG
IG 20	x					x		Packages	Packages	Number of Failed Deliveries	SUM

Figure 6: Mapping between IGs, Objects, Fact Tables and Indicators.

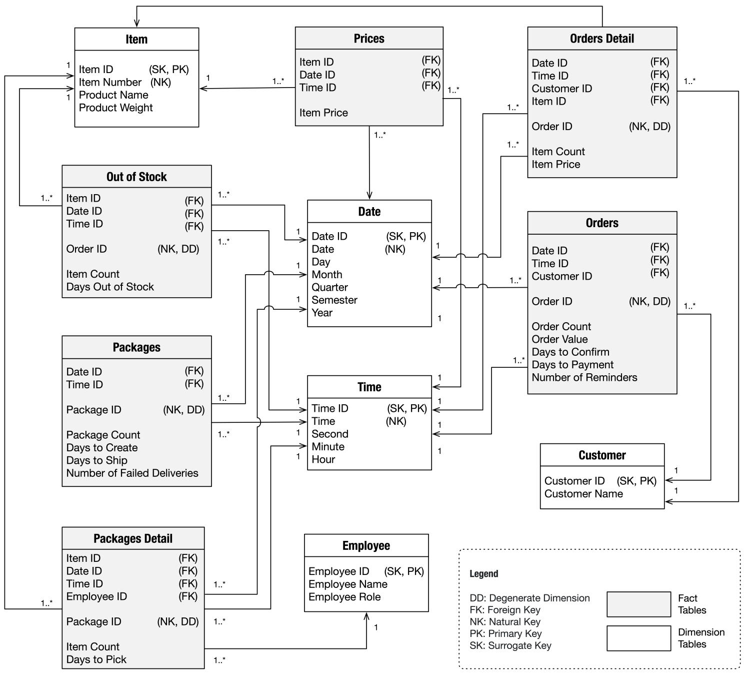

Figure 7: Analytical Data Model.

qualitative and each variable is assigned to one category. Last, the (7) Dependent type (referring to Duration) is defined as *Ratio* since it is quantitative with a unique and non-arbitrary zero point. After defining the 7 coordinates that represent the visualization context, we applied the suitability function presented in [18]. This function evaluates the degree of suitability (fit, acceptable, discouraged, unfit) of each visualization type for each coordinate value.

We present three types of visualizations for brevity, though all were evaluated. Based on the suitability scores in Table 1, the most appropriate visualization for IG 17 is a Multiple Line Chart.

Table 1

Example of visualization suitability scores for IG 17.

IG 17

Vis. context	**Mult. Line**	**Stacked Column**	**Bubble graph**
(1) User: Tech	fit	fit	fit
(2) Vis. Goal (VG): Comparison	acceptable	fit	fit
Trend	fit	discouraged	acceptable
(3) Interaction (IT): Overview	fit	acceptable	fit
(4) Dimensionality: n-dim.	fit	fit	fit
(5) Cardinality: Low	fit	fit	acceptable
(6) Independent type: Nominal	fit	fit	unfit
(7) Dependent type: Ratio	fit	fit	fit

4. Running Example Evaluation and Discussion

In this section, we evaluate and discuss the effectiveness of the proposed methodology through the analysis of the obtained dashboard. This dashboard is designed to support the analytical tasks identified in the methodology and demonstrate how the DGs are effectively supported.

Overall, the dashboard (Figure 8) presents insights into the evolution of package and item quantities over time (IG 13 and IG 14), out-of-stock (IG 12) and failed deliveries (IG 20) rates, processing times at various stages of the order fulfilment process (IG 15, IG 16, IG 18 and IG 19), and the evolution of package creation time and out-of-stock days for items (IG 17). These visualizations provide key insights into organizational performance and process efficiency, highlighting how different factors interact and affect overall operational effectiveness.

Figure 8: Dashboard of SG Decrease Processing Cost.

Figure 8 shows the relationship between the IGs defined above. IG15, IG16, IG18, and IG19 compare the average days taken for different stages of order processing, such as order confirmation, item picking, order sending, and package creation. This comparative analysis reveals that the time taken to create a package is significantly higher, indicating a bottleneck in the process. This bottleneck is further examined through IG17, which shows the impact of out-of-stock items on package creation time. The correlation identified here demonstrates how inventory issues can lead to delays in package processing, contributing to overall inefficiency. By addressing these stock-out issues, the organization can streamline package creation, thereby reducing overall processing times. Although the prices of each process are not reflected in the data, it is assumed that this reduction in time results in lower costs for the organization. These insights directly contribute to the SG's decreasing processing costs. The organization can implement targeted improvements by addressing the inefficiencies highlighted in IG15, IG16, IG18, IG19, and IG17. Reducing the time taken for package creation, minimizing stock-outs, and improving inventory management are key steps toward achieving this strategic goal.

From an operational perspective, achieving this SG does not require a complete redefinition of the process model but may involve adjusting specific elements. For example, introducing a "Stock Verification" activity before the "Confirm Order" step could enhance process efficiency. This adjustment ensures that inventory levels are checked before accepting orders, which can help reduce package creation time, as it guarantees that there is sufficient stock for all accepted orders. Such targeted modifications can improve overall operational effectiveness without requiring a comprehensive overhaul of the existing process model. As Figure 8 shows for IG 12, the global rate of out-of-stock items is ≈21% complementing the findings highlighted for IG 17.

IG 20 points to another inefficiency in the operational process. More than 27% of failed deliveries represent financial costs for re-sending the packages but also negatively impact the image of the organization, with delays in delivering the products to customers (Figure 8).

For IG 13 and IG 14, while the number of packages sent remains stable (IG 13 - blue line), the number of items per package varies significantly (IG 14 - red line). This suggests that some packages may be sent with only a few items, likely due to stock-outs. Filtering by the highest average number of items per package shows that around 16% of the products were out of stock, while the lowest average shows this value rising to around 22%, highlighting the influence of stock-outs in packages' composition. To avoid this, the items' availability could be communicated to customers when confirming orders to avoid sending multiple packages for the same order. Although this may slightly delay delivery, the reduction in shipping costs and the adoption of more sustainable policies are clear benefits. It would also be important to monitor the impact of these changes on customer satisfaction and behavior, especially concerning the volume and frequency of orders. For urgent products, separate shipping of packages can be maintained, ensuring operational benefits without compromising the customer experience.

Without this analytical approach, the nuanced insights into bottlenecks and inefficiencies would remain unknown, hindering our ability to make targeted improvements. The methodology and dashboard analysis have been crucial in identifying specific areas for operational enhancement that were otherwise unrecognized. This evaluation of the proposed approach highlighted how highly detailed operational data can complement business process data, enhancing decision-making that targets specific SGs. These SGs, from the analytical perspective, aim for descriptive, diagnostic, or prescriptive analyses for DGs that enhance efficiency and efficacy. The proposed approach guides these improvements by considering IGs for the analysis of specific business or process indicators. As seen in Figure 8, all IGs were properly integrated into a dashboard considering best practices for analytical visualization.

5. Conclusions

This paper proposed a methodological approach to integrate BA and PA to enhance data-driven decision-making within organizations. By systematically combining these analytical domains, our approach enables a deep understanding of how process inefficiencies impact business performance and vice versa, providing a comprehensive view of organizational operations and improving decision-making processes. The outlined methodology includes structured steps such as process modeling and understanding, conceptual data modeling, defining analytical requirements, developing an analytical data model, and developing effective visualizations. As a contribution, the proposed steps are valuable for systematically transforming raw process data into useful information, and identifying inefficiencies and opportunities for improvement.

The approach was evaluated through a dashboard that demonstrates its effectiveness in supporting analytical tasks and achieving strategic goals. The dashboard offered insights into several operational indicators, such as package and item quantities, out-of-stock rates, failed deliveries, and processing times, uncovering bottlenecks and inefficiencies that, when addressed, could significantly enhance operational performance and reduce processing costs.

Our findings emphasize the importance of integrating business and operational data to uncover hidden inefficiencies and support informed decision-making. The dashboard analysis showcased how detailed operational data complements business process data, providing a nuanced understanding of organizational dynamics. The proposed approach and resulting visualizations illustrate how targeted improvements can be achieved without overhauling existing process models, thus enhancing overall efficiency and effectiveness.

For future work, simulation techniques will be used to generate additional data for the process. This allows the analysis of the monetary cost of processes and their activities, for instance. Moreover, current requirements can be further detailed to better highlight the relationships between objects and activities. The proposed approach can also support process enhancement with process mining or simulation, facilitating the quantification and evaluation of the benefits of the proposed changes. Finally, although the proposed approach was tested using a classic example, its underlying principles are adaptable to a wide range of domains. Testing the approach in complex real-world contexts and diverse industries will further demonstrate and evaluate its comprehensiveness and practical applicability across diverse operational contexts.

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