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A Strategic Review of Data Fusion Abstraction Levels for Corporate Pricing Optimization

Nathan Isaac Suchar Ponte

Engagement Manager, Miami, FL.

Abstract

In the era of digital commerce, corporate pricing strategy consistently relies on data integration. While vast access to data repositories has become standard practice for most companies in 2025, the architectural methodology to integrate these disparate data signals is yet to be understood and utilized in the corporate world beyond technical executives.

This review bridges the gap between technical data techniques and commercial strategy by evaluating Data Fusion through the "Levels of Abstraction" framework: Low-Level (Data-Level), Medium-Level (Feature-Level), and High-Level (Decision-Level).

A comparative analysis of three distinct corporate scenarios is performed, outlining how Low-Level Fusion is a technically superior approach, but only fit for the select subset of organizations that possess digital-native ecosystems with high-fidelity raw data. Medium-Level Fusion is regarded as ideal for omnichannel retailers requiring interoperability between internal data and third-party vendor information. Finally, High-Level Fusion is identified as the most effective strategy for legacy organizations, prioritizing robustness over granularity. It is concluded that effective pricing optimization requires aligning the fusion architecture with the organization's data maturity and specific resources and needs.

Keywords: *Data Fusion, Corporate Pricing, Algorithmic Pricing, Data Abstraction.*

INTRODUCTION

In modern commerce, high-level executives continuously rely on accurate data analytics to inform critical decision making, from everyday decisions (e.g., deciding where to deploy a customer service team) to long-term implication decisions like how to price thousands of products and services.

In 2025, large-scale enterprises rarely struggle to access the information they need to inform executive dashboards, but rather, the main barrier for painting an accurate picture of the status quo is seamlessly combining vast data from heterogeneous sources and formats such that all signals can interoperate and work together to reach a unified conclusion [1].

While recent Data Fusion technological advancements have increased analytic capability to solve the critical issue of merging disparate data sources into single vectors, a lack of relatability with non-technical users results in low levels of adoption among corporate users.

This paper aims to bridge the gap between the technical and corporate worlds in the aspect of Data Fusion through an extensive review of the "Levels of Abstraction" framework proposed by Federico Castanedo [2], and proposing specific scenarios in which corporate entities can take advantage of this technology, with a specific focus on the pricing optimization domain.

DATA FUSION TECHNIQUES

In this review, the definition of Data Fusion is leveraged from Hall and Llinas [3]: *"data fusion techniques combine data from multiple sensors and related information from associated databases to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone".*

While Data Fusion can be classified in several ways, this review focuses exclusively on the Level of Abstraction [2]. This classification is most relevant for corporate pricing strategy as it allows for a pragmatic application in which companies can inform decision-making with varied levels of data fidelity.

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Low-Level Fusion

Low-Level Fusion requires the lowest level of abstraction and refers to the instances in which multiple sources contain largely homogenous data which can be easily compiled, processed and interpreted without major structural manipulation. This technique requires that input data be commensurate, with formats being highly compatible. A paradigmatic application yielding high-fidelity results is the fusion of pixel data being sourced from two different cameras with images of equivalent technical settings.

From a strategic perspective, Low-Level Fusion is the most rigorous and methodologically sound approach, since data is being sourced directly from the origin, allowing for the most granular analysis to take place. However, this precision is not without cost: it requires substantial processing power and storage infrastructure, as the central processing unit handles individual data points from the source and analyzes at the lowest possible level of granularity.

Medium-Level Fusion

Medium-Level Fusion is a technique that requires at least one layer of abstraction, in which individual sensors collect data and perform local processing before sharing it, synthesizing the information into representative features before integration [2]. A flagship example of when this technique is highly valuable is the evaluation of customer sentiment. Rather than integrating every individual customer review into a mathematical model, the customer review is synthesized into a limited set of attributes that characterize the "sentiment score" of that day or product. Unlike in Low-Level fusion, this level of abstraction allows for the integration of disparate data, such as combining financial metrics with demographic data [2].

At this fusion level, a significant burden is lifted from the processing power unit, as processing is performed at the sensor level, significantly reducing the IT investment required for the practical use of this technique. Despite this level of abstraction, the output remains high-fidelity as long as the critical attributes are representative of the most critical variables that influence pricing decisions, making Medium-Level Fusion the optimal balance between data richness and processing efficiency.

High-Level Fusion

High-Level Fusion, often referred to as "Decision-Level Fusion" requires the highest level of abstraction, and is a technique in which decisions, and not data, are fused to reach a conclusion. In this instance, each data source processes and reaches a solution individually. All of these decisions are ultimately forwarded to a central fusion node, which applies decision logic to generate a final global command. A prime situation in which High-Level Fusion is leveraged is when companies have completely different architectures for their "Discounting" and "Clearance" programs. While the discount engine might recommend a price increase, the clearance engine might propose a conflicting adjustment, and since data cannot be feasibly fused, individual engines and decisions are made and finally combined in a single node to weigh the information and make a call.

The primary advantage of high-level fusion is structural robustness and fault tolerance [4]. Since data input and processing happens separately, the failure of an individual source or logic does not corrupt the entire system, and the central node can weigh and ignore erroneous input. This makes high-level fusion favorable for legacy corporations, where data quality tends to be low fidelity. The downside of using high levels of abstraction is losing all visibility into the correlation between the raw data inputs, potentially missing market signals that could otherwise be considered.

Table 1. Summary of Data Fusion Techniques by Level of Abstraction

Level of Abstraction	Technical Definition
Low-Level	The immediate synthesis of raw data from multiple sources prior to any significant processing or feature extraction.
Medium-Level	A process where individual data sources are first pre-processed to extract representative attributes, which are then concatenated into a variable for model input
High-Level	The integration of independent decisions or probabilities generated by separate, domain-specific models to reach a final global inference.

LEVERAGING DATA FUSION TECHNIQUES IN CORPORATE CONTEXTS

Corporate analytics teams need to consider data accessibility, quality, and homogeneity to decide which Data Fusion Technique is right for their organization. Thinking about the following three typical corporate scenarios in modern commerce can help analytics teams make a decision:

High-Fidelity Raw Data Access

In this scenario, the organization typically has access to several high-fidelity sensors, which allow them to capture all raw data required to inform the pricing strategy. These companies often possess end-to-end ownership of their data infrastructure. This scenario is characteristic of digitally native or Direct-to-Consumer (D2C) platforms (e.g., Amazon, Shopify) where the ecosystem is closed and standardized [3]. For example, a D2C e-commerce platform can independently measure web traffic, cart abandonment rates and conversion rates without the need for third-party sourcing.

In these scenarios, because the data is owned end-to-end by the same entity, the datasets typically share the same internal infrastructure, resulting in highly commensurate and synchronized data, which makes this the ideal scenario for leveraging Low-Level Fusion as the optimal pricing strategy. Fusing the raw signal allows the pricing algorithm to detect correlations between traffic spikes and price elasticity that would be lost if the data were summarized into features first [3].

Hybrid: Internal and External Datasets

This scenario represents the most common challenge for omnichannel retailers, where it is typical to have significant high-quality internal data (e.g., POS sales, inventory levels), but third-party information is needed to complete the picture that influences pricing decisions (e.g., purchasing competitor pricing from NielsenIQ, consumer sentiment from social listening tools, or foot traffic around store area).

In this case, the company cannot access the raw data of the third party, making Low-Level Fusion unattainable. In these situations, Medium-Level Fusion is the recommended approach. The pricing analytics teams can collect and consolidate the information from their own internal sources, but then fuse this data with the features provided by third-party vendors in order to have a working pricing recommendation engine. By creating a unified variable that combines these heterogeneous inputs, the pricing model can infer relationships between external market pressure and internal demand, balancing the inside-out and outside-in perspectives [2].

Unreliable or Conflicting Data Sources

The last scenario is one characterized by legacy infrastructure, incomplete data, or conflicting signals from several sources, which is typical for large corporations with outdated infrastructure, or during post-merger integrations where multiple incompatible systems are combined. Attempting to fuse data at the lowest level runs the risk of operating under false precision, degrading system performance. As noted by McKinsey & Company, organizations often over-invest in granular data lineage when a broader view would suffice, leading to inflated costs without proportional value increases [5].

In these environments, using High-Level Fusion is recommended. Rather than forcing incompatible data into a single engine, independent processing and decision-making should happen for each domain (e.g., a “promotion engine” vs. a “clearance engine”). Each engine processes its own data and outputs an independent result. These results are then evaluated at the executive level with support from qualitative and strategic inputs, forcing a decision beyond the mathematical answer and through a pragmatic methodology. This approach aligns with McKinsey’s findings that “pulling back on granularity” can significantly reduce architectural complexity while maintaining decision quality for 80% of business cases [5].

Table 2. Summary of Strategic Data Fusion Selection

Scenario	Description	Recommended Fusion Level
Digital Native Ecosystem	Organization possesses end-to-end control of infrastructure with access to high-fidelity, commensurate raw data	Low-Level
Omnichannel Integration	Organization combines internal proprietary data with heterogeneous third-party metrics where raw data is inaccessible.	Medium-Level
Legacy Systems and M&A	Data landscape is characterized by “high noise,” including gaps or conflicting signals	High-Level

CONCLUSION

The selection of a Data Fusion technique is a fundamental strategic decision that corporate organizations should weigh thoroughly to optimize pricing effectiveness.

This review suggests that choosing a Data Fusion technique, rather than being a one-size fits-all answer, heavily depends on the individual needs and characteristics of each organization. Rather than focusing on the best mathematical answer, pricing analytics teams should focus on optimizing the precision-to-cost ratio, while also recognizing that not all companies are able to support the same level of investment.

For digital-native firms with homogenous infrastructure, Low-Level Fusion is the gold standard, unlocking the ability to detect correlations in raw user behavior. However, for the majority of enterprises, pursuing such granularity might be wasteful and result in false precision at a prohibitive cost. Companies can often achieve better operational outcomes by accepting higher levels of abstraction and avoiding the typical “granularity trap” in digital transformations [5]. Ultimately, the role of the corporate leaders is to diagnose the organization’s data maturity and select the fusion level that delivers actionable intelligence without exceeding cost-benefit thresholds.

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