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# An Integrated Big Data Analytics Architecture for Resilience: A Case Study of Last-Mile Agri-Food Delivery

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**Abstract**

In the wake of global crises and the rising need for robust supply chains, this study delves into the role of big data analytics in agri-food logistics. Emphasizing the need for uninterrupted access to essential food supplies, we use a case study approach to outline the requirements for a comprehensive big data solution. This solution, which includes descriptive, predictive, and prescriptive analytics, is based on industry standards, academic research, and the specific needs of a large B2B2C last-mile food delivery company. The proposed system architecture enhances resilience by integrating these three types of analytics, enabling improved anticipation, response, and recovery from supply chain disruptions.



*Keywords:* Agri-food supply chain; Big data analytics; Last-mile delivery; Social-ecological resilience; Sustainability; System architecture

## 1. Introduction

Last-mile delivery (LMD) in food retailing, particularly as part of the agri-food supply chain (AFSC), is a critical component in the journey of a product from the warehouse to the customer's doorstep [1]. This process is particularly important in the context of home-delivery-oriented AFSCs, where small and medium-sized agri-food enterprises collaborate to form alliances. These alliances aim to establish a stable foothold in the emerging e-commerce market by implementing strategies that cover aspects of last-mile chain extension, food transportation, and

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production/distribution control [2]. According to FarEye [3], while most U.S. consumers typically wait two to three days for digital orders to arrive, more than one-third (38%) would prefer to only wait one day or less for delivery. That's why companies are developing new technologies and experimental supply chain models to increase package volume and speed delivery. The design choices for such strategies often depend on various factors such as population density, ability to integrate cross-channel processes, and customer behavior [4].

Resilience in the AFSC and its LMD is critical to maintaining food security and ensuring the smooth functioning of the food system, especially in the face of disruptions [5][6]. It refers to the collective ability of AFSC stakeholders to ensure an acceptable, sufficient, and stable food supply by accurately anticipating disruptions and employing strategies that delay the impact, facilitate rapid recovery, and allow for cumulative learning after the disruption [6]. In the context of LMD, resilience is the ability to adapt and respond to unforeseen challenges, ensuring that food reaches the end consumer efficiently and effectively [7]. This resilience is particularly important in times of crisis, such as during a pandemic, when supply disruptions, labor shortages, and logistical challenges can significantly impact the AFSC [5][8].

On the one hand, the industry faces the challenge of meeting evolving consumer expectations for fast and flexible delivery options. The industry also needs to manage fluctuations in food demand, driven by the growing preference for organic food and the shift to e-commerce business models [9]. The ability to effectively manage disruptions, including traffic flow issues and accidents, is a critical aspect of resilience in last-mile distribution operations [10]. On the other hand, the growing carbon footprint of LMDs, which is expected to increase by 36% by 2030 [11], requires sustainable strategies to mitigate $CO_2$ emissions and traffic congestion. Regulatory measures aimed at reducing urban $CO_2$ emissions, such as vehicle bans in city centers, further complicate the operation of LMDs, requiring adaptive and resilient strategies. A resilient system can make a significant contribution to waste reduction, as 30% of the world's food is wasted and $CO_2$ emissions from transport are increasing [9]. Resilience in LMD is therefore not only a requirement, but a necessity for demand management, disruption handling, sustainability, regulatory compliance and waste reduction in food retailing.

According to the literature (e.g., [12][13]), a powerful tool to strengthen AFSC against disruptions and significantly improve resilience is big data analytics (BDA). BDA is the process of collecting, examining, managing, processing, and exploiting large amounts of data from multiple sources in a variety of formats, including structured, semi-structured, or unstructured. It aims to extract valuable insights, predict trends, support decision making and enable organizations to make strategic decisions based on concrete information. In the context of AFSC and LMD, it can analyze food quality, storage conditions, weather patterns, and even the presence of food hazards [14]. This data-driven approach enables improved operational efficiency, enhanced food quality and safety, and the development of a sustainable food ecosystem [15]. It also helps optimize operating costs, enable competitive pricing, implement dynamic pricing strategies, capitalize on data-driven up-selling opportunities, optimize inventory management, monitor performance, and improve customer satisfaction.

Despite the recognition of the advantages of BDA, there remains a gap in the integrated application of its three types [16]. Bringing them together under a single architecture could take LMD to new heights, not only providing a triple lens for assessment, anticipation, and action, but also creating a continuous cycle of improvement. Improved decision making, enhanced visibility into supply chain dynamics, and proactive problem solving are among the benefits this holistic approach can provide [17][18]. Such convergence also promises increased efficiency, a vigorous response to disruptions, and a robust paradigm for managing resources, reducing waste, and optimizing delivery. The core of this paper lies in its effort to bridge this research gap by proposing an integrated BDA model tailored to food LMDs, thus making a substantive contribution to the field. This raises the main research question: what is the optimal architecture for an integrated BDA system that enhances the resilience of food LMDs in the AFSC? Exploring this question promises to open up new avenues for understanding and enhancing the resilience of LMDs, thus setting the stage for more effective strategies in the face of disruptions.

The remainder of this paper is organized as follows: Section 2 lays the theoretical groundwork by reviewing both the academic and practitioner literature, particularly existing standards and frameworks. Section 3 is dedicated to the case study, grounding the theoretical discussion in real-world practice. In Section 4, different architectural views of the target system are designed. Sections 5 then moves into discussion and conclusion, drawing insights from the case study into broader practice and reflecting on future directions for research at the confluence of BDA and LMD resilience.

## 2. State-of-the-art

### *2.1. Scientific Literature*

The existing scientific literature on architectural frameworks and conceptual designs for BDA can be divided into three groups. The first group focuses on the design of reference models and general software architectures in the field of BDA. Notably, Kaufmann [19] proposes a big data management reference model that harmonizes technical and business aspects and supports both descriptive reporting and predictive analytics. The second category focuses on the design of BDA systems that are resilient. In this context, Shah et al. [20] present a reference model that integrates BDA and the Internet of Things (IoT), prioritizing predictive analytics. This model emphasizes the use of these technologies to predict, understand, and monitor disaster situations, with the main goal of facilitating timely decision making in crisis scenarios.

The third group of literature addresses the architecture of BDA within specific domains. Park et al. [21] introduce a reference model tailored for BDA in retail shipping decisions, emphasizing both descriptive and prescriptive analytics. Grambau et al. [22] outline a technical architecture focused on predictive maintenance, integrating social media data with existing product and service data to improve analytical models. Ma et al. [23] propose a technical architecture for a data-driven framework for sustainable intelligent manufacturing in energy-intensive industries, using predictive and prescriptive analytics to improve energy efficiency. Gyulai et al. [24] contribute a reference model for industrial data analytics, highlighting descriptive analytics through dashboards and predictive analytics for lead time and quality prediction, specifically addressing the challenge of effective use of shop floor data. Moreover, Keates et al. [16] provide a high-level conceptual overview of a multi-perspective supply chain analytics framework, emphasizing its importance in strategic decision making for AFSCs. Although this model covers descriptive, predictive, and prescriptive aspects, it lacks a detailed system design.

While the models reviewed contribute valuable designs for specific types of analytics within big data, none, with the exception of Keates et al. [16], comprehensively integrates all three. The latter emphasizes the importance of integration, recognizing its significance in achieving a holistic understanding and use of big data. However, it is notable that this model lacks detailed explanations of how such an integrated solution works. This literature review highlights the critical need for a comprehensive approach that seamlessly integrates the three types of analytics to unlock the full potential of big data. Notably, a significant portion of the research in this area, particularly within the third category, focuses on processes and sub-areas of the supply chain, such as production and transportation. This underscores the central role of BDA in the supply chain and highlights the urgency for a solution architecture that can deliver the envisioned benefits of such a system in an integrated and cohesive manner.

### *2.2. Standards and Practical Frameworks*

A big data architecture reference model provides a framework that defines the components, processes, and technologies needed to capture, store, process, and analyze big data. It typically includes layers such as data collection and ingestion, data processing and analytics, data visualization and reporting, and data governance and security. The benefits of such a model include the ability to make better and faster decisions, the ability to process and analyze more data, and the ability to improve operational efficiency. It also discusses reference models for performance, business, application, data, infrastructure, and security views.

The NIST big data interoperability framework presents the conceptual model of the NIST big data reference architecture (NBDRA) [25]. It discusses the roles and fabrics of the NBDRA, presents an activities view of the NBDRA to describe the activities performed by the roles, and presents a functional component view of the NBDRA that includes the classes of functional components that perform the activities. The ‘activities view’ describes the activities performed by different roles. The ‘system orchestrator’ manages the overall operation of the system. The ‘big data application provider’ and the ‘big data framework provider’ are responsible for data collection, preparation, analytics, and visualization. The ‘management fabric activities’ oversee system operations, while the ‘security and privacy fabric activities’ handle system security and privacy. The ‘data provider’ delivers the data, and the ‘data consumer’ consumes the data. These roles work together to ensure the smooth operation of the big data system.

ISO/IEC 20547 specifies the big data reference architecture (BDRA) [26]. The reference architecture contains concepts and architectural views. It defines two architectural views: a user view that defines roles/sub-roles, their relationships, and types of activities within a big data ecosystem; and a functional view that defines the architectural layers and the classes of functional components within those layers that implement the activities of the roles/sub-roles within the user view. The ‘big data application’ layer is responsible for implementing the business logic and providing the user interface. The ‘big data processing’ layer handles data processing, including data cleansing, transformation, and analysis. The ‘big data platform’ layer provides the infrastructure for data storage and processing. The ‘resource’ layer includes the physical resources, such as servers and networks, that support the big data system. The ‘multi-layer functional components’ span multiple layers and provide functionalities such as security, privacy, and management.

These reference models can be used in the design of new integrated systems by providing a common language for different stakeholders, encouraging adherence to common standards, specifications, and patterns, and providing consistency in the implementation of technologies to solve similar problems. They facilitate the understanding of the operational intricacies of big data and illustrate and understand the various big data components, processes, and systems in the context of an overall big data conceptual model. They also provide a technical reference for government agencies and other consumers to understand, discuss, categorize, and compare big data solutions.

## 3. Case Study

### *3.1. The Background of the Case Company*

The case study focuses on a leading LMD food company in the Middle East, established in the 2010s. The company operates on a B2B2C model, acting as an intermediary between food suppliers and consumers. It offers a wide range of daily essentials, including groceries and kitchen essentials, through its extensive platform. Customers can easily purchase these items through a mobile or web application and have them delivered directly to their homes. The platform encourages user engagement through product ratings, reviews, and social networking, and offers significant personalized discounts on various items. This approach has set a precedent in grocery retailing in several countries.

Currently, the company uses descriptive analytics, leveraging a data warehouse and Power BI dashboards, to understand consumer behavior and market trends. This information is critical to making informed decisions about product availability based on customer preferences and buying patterns. However, the company is undergoing a technology transformation, integrating predictive and prescriptive analytics to refine its approach to effectively meet evolving market demands. Predictive analytics is used to forecast demand and optimize inventory, while prescriptive analytics provides insights to streamline logistics for timely LMDs. This integration of analytics is critical for the company to improve forecasting, inventory management, and operational efficiency.

### *3.2. Strategic Drivers of the Future System*

In our study, which included 17 semi-structured interviews with the case company’s board members, CXO-level managers, and business consultants, we identified seven critical strategic drivers that necessitate the integration of an advanced analytics architecture for improved resilience in agri-food LMDs. To validate our findings, we employed a triangulation approach [27] by cross-referencing the identified strategies with the company’s strategic plan, management meeting minutes, business system reports, business intelligence dashboards, and employee feedback. Table 1 shows the extracted strategic drivers.

### *3.3. Main Requirements of the Future System*

Based on insights gained from interviews, evaluation of current systems, stakeholder feedback, and industry best practices, the design of the target system should include both functional and non-functional requirements. Functional requirements, outlined in Table 2, are essential operations that affect system effectiveness and user satisfaction. Non-functional requirements, listed in Table 3, evaluate system performance, focusing on quality and operational characteristics. These requirements are critical to the robustness, efficiency, and adaptability of the system, ensuring that it meets user expectations and industry standards while remaining flexible to changing conditions.

Table 1. The critical strategic drivers identified in the interviews.

| Strategic driver | Description |
|---|---|
| Supply chain visibility and transparency | The company is improving supply chain visibility by monitoring goods movements and inventory levels in real time to proactively mitigate disruptions. Leveraging historical data, it is integrating predictive analytics to anticipate potential inefficiencies, contribute to resilience, and align with visibility goals. In addition, it is exploring prescriptive analytics to recommend actions for visibility, strengthening the resilience and proactive adaptability in its supply chain. |
| Demand forecasting and planning | Now using descriptive analytics to understand historical sales data, the company aims to improve demand forecasting by taking into account historical trends, market conditions, and external factors. This approach increases resilience by enabling proactive responses to demand fluctuations. The company also wants to optimize inventory planning to ensure sufficient inventory while minimizing excess inventory. It is interested in a recommender system that suggests inventory adjustments, improving efficiency and resilience by providing insights to effectively manage potential inventory issues. |
| Risk management and mitigation | The company seeks to proactively model and predict potential risks using historical patterns and external factors, with the goal of increasing resilience through prescriptive analytics. This strategy considers a range of challenges, including geopolitical conflicts, natural disasters, and pandemics. The goal is to build resilience to disruptions and ensure a proactive response to unforeseen events. The company is committed to building a resilient LMD system that can adapt and respond effectively to various challenges and enhance operational continuity. |
| Operational efficiency and optimization | The company strategically streamlines operations by optimizing logistics, distribution, and resource allocation to enhance efficiency, resulting in cost savings, faster response times, and improved supply chain performance. Descriptive analytics is used to analyze historical data, identify inefficiencies, and understand past challenges. Predictive analytics will anticipate future operational challenges and proactively optimize logistics and distribution. Prescriptive analytics will recommend actions to streamline operations and improve resource allocation. This focus on operational optimization is key to building a resilient delivery framework that can adapt to changing circumstances and ensure a robust, efficient supply chain. |
| Customer-centric approaches | The company tailors its offerings to customer preferences, improving the customer experience and fostering loyalty. It uses descriptive analytics to analyze historical data and understand customer behavior, and predictive analytics to forecast future trends. This enables the company to deliver personalized services that meet evolving customer needs. The company plans to integrate prescriptive analytics to recommend actions based on predicted customer preferences, further enhancing customer satisfaction. This customer-centric approach contributes to a resilient delivery framework that adapts to changing demands and strengthens the company's competitive position. |
| Agility and flexibility | The company aims to develop flexibility in its delivery network to adapt to market changes. It plans to use descriptive analytics to identify past agility instances and challenges, predictive analytics to anticipate disruptions or market shifts, and prescriptive analytics to recommend adaptive strategies. This focus on agility aligns with resilience, enabling the company to navigate uncertainties, strengthen adaptability, and maintain efficiency amid changing market dynamics. |
| Sustainability and resource optimization | The company emphasizes sustainable practices and resource optimization to promote resilience and meet environmental and social responsibility goals. Its goal is to use descriptive analytics to assess historical resource use and identify areas for improvement, predictive analytics to forecast resource needs and environmental impacts, and prescriptive analytics to recommend sustainable practices. This approach can enhance sustainability efforts, contribute to operational resilience, and ensure responsible resource use in the face of environmental challenges. |

Table 2. Functional requirements for the integrated BDA system.

| Function | Requirements |
|---|---|
| General functions | (i) Support various stakeholders' roles, including logistics managers, inventory controllers, demand planners, risk managers, operations teams, customer service, marketing teams, and executives. (ii) Seamlessly integrate and aggregate data from diverse sources, such as IoT devices, databases, web services, logs, and sensors. |
| Real-time tracking and visibility | (i) Receive real-time tracking data for accurate visibility into delivery vehicle locations, enabling dynamic route planning for efficient handling of new orders along the current route, and optimizing delivery times from the nearest warehouse. (ii) Integrate with GPS technology and geospatial data to enhance location accuracy. |
| Dynamic route optimization | (i) Dynamically optimize delivery routes based on real-time traffic conditions, weather, number of orders on the same route, etc. (ii) Utilize predictive analytics to anticipate traffic patterns and proactively optimize routes. |
| Demand forecasting for inventory management | (i) Utilize predictive analytics to forecast demand for various products in specific geographic areas. (ii) Integrate with inventory management systems to optimize stock levels based on predicted demand. |
| Customer behavior analysis | (i) Employ descriptive analytics to analyze historical customer behavior and preferences. (ii) Leverage predictive analytics to forecast future trends in consumer behavior. (iii) Implement prescriptive analytics to recommend personalized offerings based on predicted customer preferences. |

Table 3. Non-functional requirements for the integrated BDA system.

| Quality | Requirements |
|---|---|
| Scalability | (i) Accommodate varying loads during peak delivery times or seasonal fluctuations. (ii) Support the increasing volume of data generated during peak operational periods. |
| Data security and privacy | (i) Implement robust security measures to protect sensitive customer and operational data. (ii) Ensure compliance with data privacy regulations and standards. |
| System reliability and availability | (i) Ensure high system availability to guarantee uninterrupted delivery operations. (ii) Implement reliable backup and recovery mechanisms to handle system failures. |
| User interface and experience | (i) Design intuitive and user-friendly interfaces for both delivery personnel and customers. (ii) Ensure a responsive design for access through various devices, including mobile applications. |
| Interoperability | (i) Ensure compatibility with various devices, sensors, and IoT technologies used in the delivery process. (ii) Facilitate integration with third-party logistics and transportation systems. |

## 4. The Proposed System Architecture

The logical view of the proposed system architecture, illustrated in Fig. 1, includes classes in the *Business Data* package for system functionalities (Table 2) and *Analytics and Visualization* classes for seamless system interactions. Strategic drivers (Table 1) shape key entities and processes, influencing class attributes and methods in both packages. For example, the focus on process optimization includes classes for optimization algorithms and efficient data processing. The *Core* package meets non-functional requirements (Table 3). Class relationships are modeled based on class interactions that capture system functionality. The *Core* package manages data flow with classes such as `ExternalAPIClient`, `ETLProcessor`, and `DataStorage`, which includes `DataWarehouse` and `DataLakeStorage`. The Business Data package represents business entities such as suppliers, products, customers, orders, and logistics, with classes such as `SupplierProfile`, `OrderData`, and `LogisticsController`. The Analytics and Visualization package uses structured data to provide insights through classes such as `VisualizationConfiguration`, `PredictionModel`, and `OptimizationModel`.

The process view in Fig. 2 illustrates an example process realized by the system architecture, highlighting the data visualization process. The `ETLProcessor` initiates the ETL process by requesting data from the `ExternalAPIClient`, which authenticates to the `ExternalSystem` to retrieve raw data. At the same time, the `Visualizer` triggers the creation of the visualization by calling a method of the `VConfigurator`, which calls `predictOutcomes()` of the `Predictor`. The `Predictor` interacts with the `DataWarehouse` and `DataLakeStorage`, retrieves structured and native data respectively, performs model training and validation, and sends predicted data to the `VConfigurator`. `VConfigurator` customizes visualizations and sends them to `Visualizer`, demonstrating the coordination between ETL processes and predictive analytics.

The implementation view in Fig. 3 illustrates the modular organization of the system, showing system components such as data processors, analytics engines, storage, and interfaces, as well as their interconnections. It provides a high-level overview of the system architecture by introducing the key building blocks and their relationships, and helps to understand the collaborative structure and functionalities of the system. All system components are designed in the following five layers:

- *Big Data Services* layer: Central governance hub with modules for data integration, governance, quality assurance, and stakeholder alignment, ensuring seamless data flow and compliance.
- *Big Data Framework* layer: Supports communication between layers, housing data storage, processing engines, OLAP, access management, monitoring, and resource optimization.
- *Big Data Provision* layer: Entry point for data, managing connections to various sources, handling data extraction, ingestion, and metadata generation for system-wide accessibility.
- *Big Data Applications* layer: Orchestrates big data lifecycle, processing business logic, and providing descriptive, predictive, and prescriptive analytics for decision-making.
- *Big Data Consumption* layer: Interfaces with end-users, presenting analytics outcomes, and collecting feedback for system improvements and user-centric optimization.

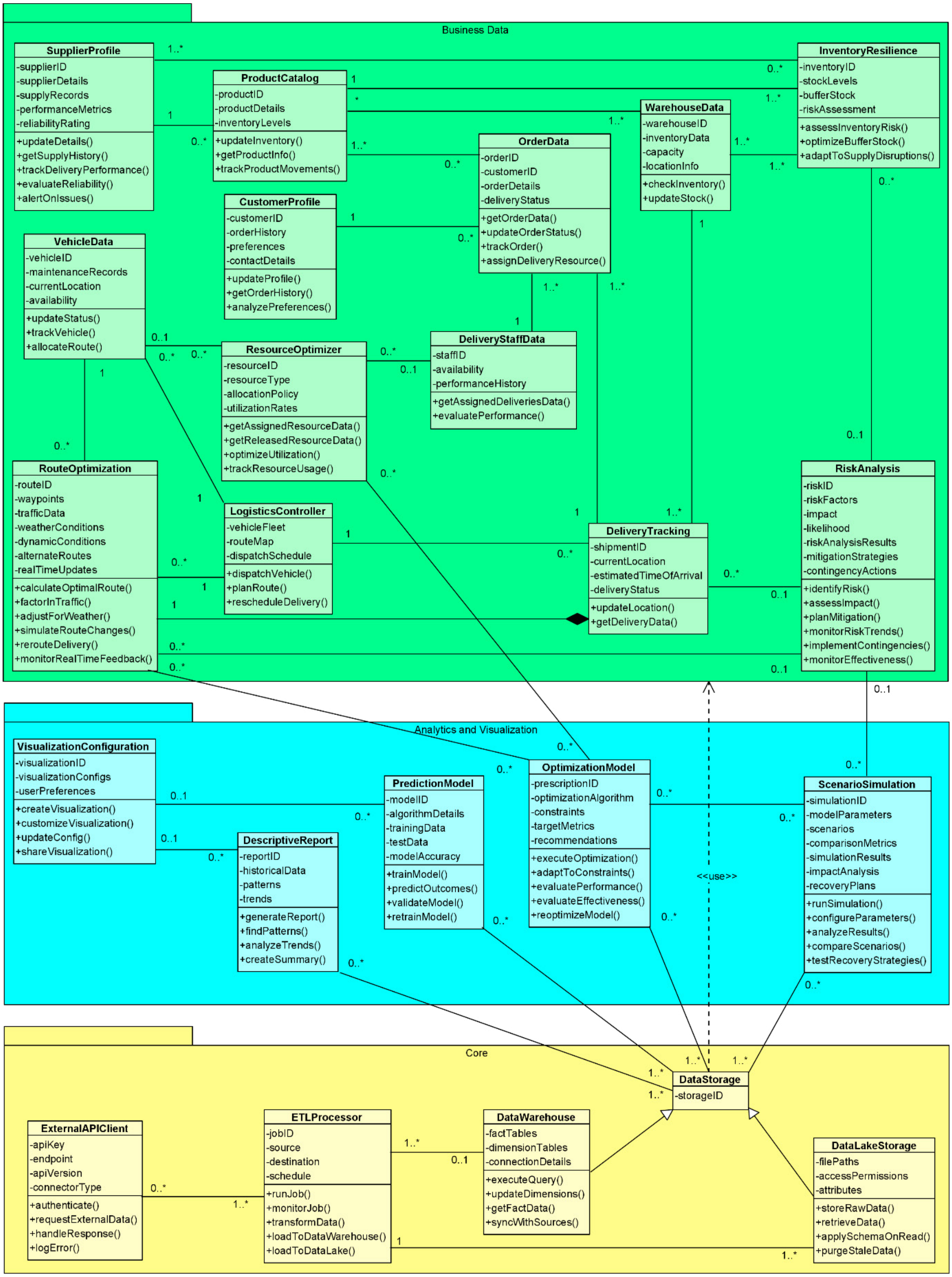


Fig. 1. The logical view of the proposed system architecture.

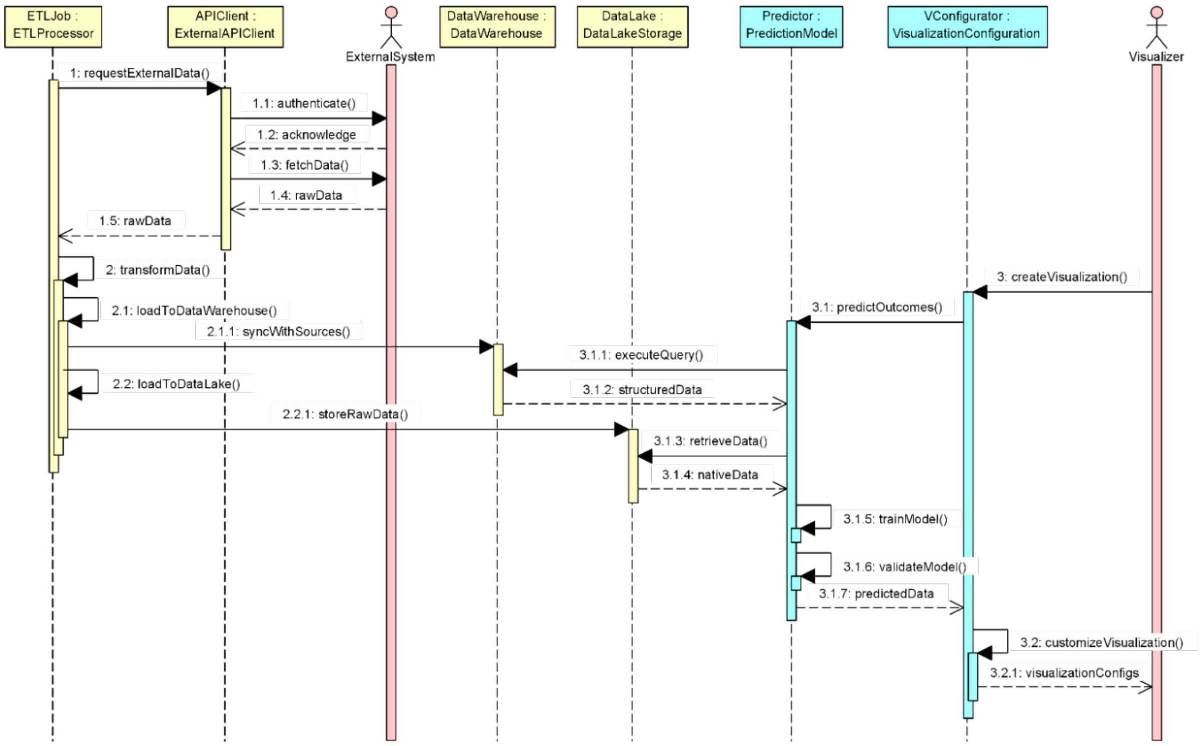


Fig. 2. The process view of steps for visualizing predictions.

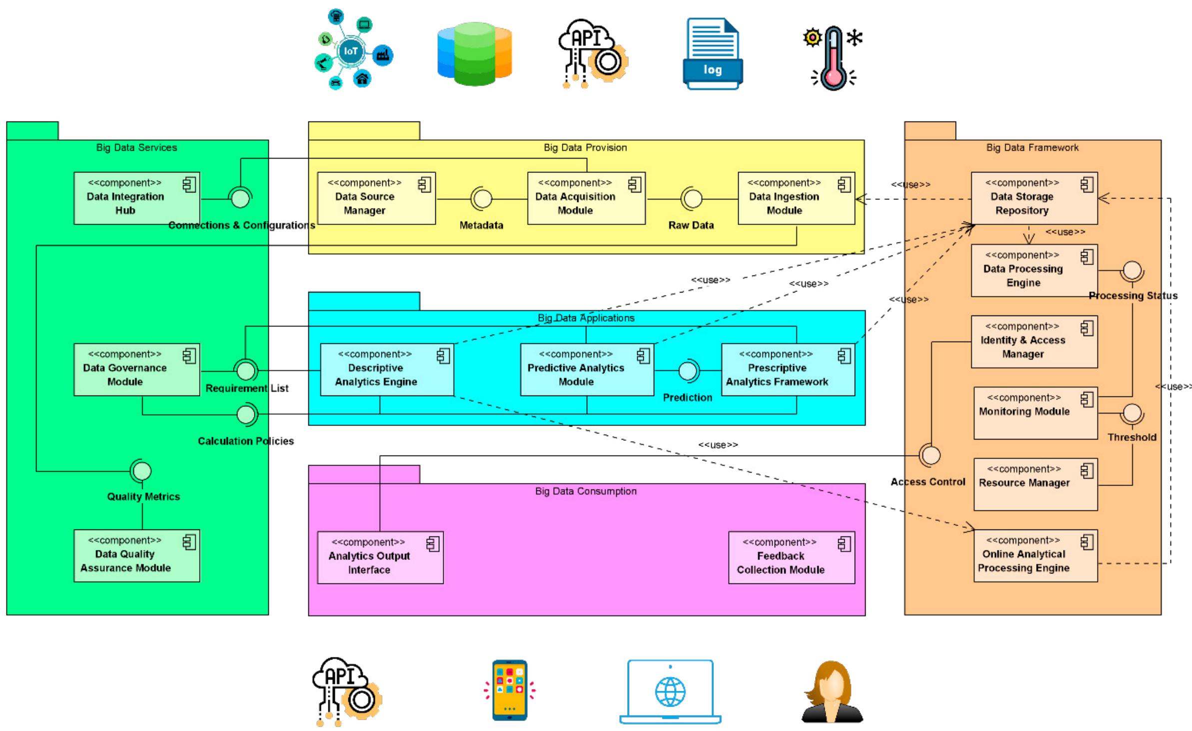


Fig. 3. The implementation view of the proposed system architecture.

## 5. Discussion and Conclusion

This paper has addressed the critical need to improve the resilience of LMDs in the face of global population growth and increasing disruptions. Leveraging the power of BDA and recognizing the importance of integrated analytics, we proposed a comprehensive model tailored for food LMDs. The case study of a food LMD company served as a practical lens, highlighting the critical role of resilience, particularly in the crucial last leg of the supply chain that impacts customer satisfaction. By conducting interviews and aligning the proposed architecture with strategic drivers, this research bridges the gap between theory and practice.

Our case study highlights the importance of integrating advanced analytics—descriptive, predictive, and prescriptive—in agri-food LMDs to enhance resilience by understanding past operations, predicting trends, and recommending optimal actions. This aligns with the literature emphasizing the synergies between types of analytics and the need for a unified approach in complex AFSCs [28][29]. We identified seven strategic drivers—visibility, forecasting, risk management, efficiency, customer-centricity, agility, and sustainability—that shape the need for advanced analytics to realize the multidimensional aspects of resilience in the sector [6][30][31]. However, practitioners primarily rely on basic analytics, necessitating a shift to advanced techniques such as machine learning and recommender systems. This transition requires systems that are scalable, secure, reliable, and interoperable [32].

Our proposed architecture provides a streamlined and efficient approach to BDA, outperforming models such as Park et al. [21]'s IRIS-RM and Keates et al. [16]'s MPSCA framework. By focusing on direct integration with big data platforms, our solution reduces complexity, increases scalability, and improves performance without adding latency or requiring extensive customization, making it adaptable to diverse business environments. Compared to Grambau et al. [22], which integrates social media data into predictive maintenance models, our architecture leverages advanced preprocessing, robust machine learning algorithms, and comprehensive data integration for more accurate predictions and scalability. Furthermore, our system enables faster decision making through real-time processing and advanced visualization. Unlike Ma et al. [23] and Gyulai et al. [24], which focus on energy optimization and manufacturing, our architecture targets supply chain resilience, emphasizing real-time decision making and feedback loops that are critical for logistics. Moreover, our architecture incorporates advanced AI and machine learning for predictive and prescriptive analytics, providing deeper insights than MPSCA, which focuses more on process compliance. We also emphasize easy-to-use interfaces and advanced visualization for better interaction, providing more robust real-time decision support compared to MPSCA's focus on process and data conformance.

The proposed architecture has not been tested with real-world data or experiments, which limits its practical applicability. Looking ahead, future research agendas could focus on refining and implementing the proposed integrated system architecture in different supply chain contexts. The case study methodology provides a starting point, but further experimental/empirical studies across industries and regions will enhance the generalizability of the proposed model. Furthermore, continuous advances in technology and data analytics require ongoing exploration of new tools and techniques to strengthen LMD resilience. Ultimately, this research lays the groundwork for the development of an analytics-driven decision-making system [33] that leverages big data from multiple sources to strengthen the resilience and adaptability of future AFSCs. A future study that identifies the most important BDA practices to make agri-food businesses more resilient seems to be of interest to both academics and practitioners. As the goal is to ensure the security and continuity of food distribution in the face of dynamic global challenges, it would be valuable for future studies to use a social-ecological perspective on resilience.

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