

A Review on Modern Trends in Digital Twin Technology in Retail Stores

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Abstract

Digital Twin (DT) technology has emerged as a transformative solution for managing the operational complexity of modern retail grocery stores. This systematic review examines seven contemporary DT methodologies applied to retail inventory management, store organization, and supply chain resilience, comparing their approaches, limitations, and practical contributions. The reviewed studies span a diverse range of technical implementations, from mathematical optimization using Wilson's Economic Order Quantity model to AI-driven computer vision pipelines combining YOLOv8 detection with Vision Transformer classification for real-time shelf mapping. Hardware-based approaches are also examined, including autonomous RFID robots achieving 99.06% inventory accuracy and portable Bayesian-filter localization systems integrated with SLAM-based 3D reconstruction. Complementing these technical studies, conceptual frameworks and qualitative case studies address broader challenges such as supermarket layout management, GDPR-compliant DT architecture design, and zero-waste sales and operations planning in grocery retail. The review identifies several persistent research gaps that constrain wider adoption: limited end-to-end value chain integration, inadequate handling of perishable goods and expiry tracking, weak privacy governance frameworks, real-time synchronization latency, and the absence of standardized performance benchmarks across studies. The COVID-19 pandemic is highlighted as a catalyst that exposed the inadequacy of traditional planning systems and accelerated demand for simulation-based resilience strategies. The findings provide both technical blueprints and strategic frameworks for practitioners and researchers, establishing a foundation for scalable, interoperable, and privacy-conscious digital twin deployment across multi-store retail environments.

Index Terms: Computer Vision, Digital Twin, Retail Inventory Management, Radio Frequency Identification, and Supply Chain Resilience.

I. INTRODUCTION

The complexities of the retail grocery store operation are extraordinary. One large supermarket could have 20,000–40,000 different Stock-Keeping Units (SKUs), hundreds of customer interactions are happening every hour, replenishment of stock is ongoing, seasonal variation in demand can be as much as 50% and margins can be less than 5% – meaning that even a marginal efficiency gain is worthwhile. Barcoded systems, manual stock taking and spreadsheets are no longer up to the task of such complexity. Digital twin technology provides an attractive alternative – a real-time virtual model of the store that can track inventory, simulate the layout, predict demand, warn employees of stockouts, and assist customers in navigating the store [1]. A digital twin is not just a 3D model (or simulation) of a physical object, it is a continually updated representation, which is synchronized with the real world counterpart by exchanging data in both directions, usually using the Internet of Things (IoT) sensors, cloud computing and data analytics engines. There are three main components of any Digital Twin (DT): (1) the physical object, (2) its digital representation, and (3) the data flows that maintain the synchronization between the physical and

digital. The enabling technologies that enable modern DT systems are diverse. They encompass a range of technologies, such as Radio Frequency Identification (RFID) for item-level tracking, computer vision and deep learning for visual recognition and scene reconstruction, Simultaneous Localization and Mapping (SLAM) algorithms for spatial awareness, Augmented and Virtual Reality (AR/VR) for visualization, and simulation engines for scenario planning. As these technologies combine, the accessibility to deploying functional digital twins in real operational environments, such as physical retail stores [2] has dropped significantly.

A. The Covid-19 Pandemic Aftermath

The effects of the pandemic have been illustrated in research that has shown how digital twin-based simulation could have predicted these disruptions, and guided more resilient response strategies. Discrete-event simulation models of multi-stage food retail supply chains can then be stressed against pandemic scenarios—during times of peak demand, or factory closures, or transport delays—and the researchers have been able to measure the impact of each type of disruption and to prioritize the interventions that are most cost-effective to make the supply chain more



resilient. This study has definitely proved the importance of DT technology on the day-to-day efficiency and preparedness of the system for a systemic shock. In addition to crisis response, the pandemic has also catalyzed the structural evolution towards real-time inventory visibility. Rapidly changing consumer habits outpaced conventional weekly cycle counts, creating an urgent need for real-time inventory visibility solutions. Consumers' buying habits were moving quickly and erratically and conventional systems were not keeping up with weekly cycle counts. This need was the logical technological solution to digital twins that are able to represent the shelf status in almost real time using computer vision and RFID [3].

B. Identified Research Gaps

Although there have been significant advances in recent years, the current DT systems show some important research gaps that inhibit widespread use and usefulness of this technology in retail grocery shops. Insufficient level of integration in the value chain: Most studies deal with either the store or the supply chain. There are not many systems available that offer full integration from suppliers to store shelves [4]. Lack of perishability management: DT systems currently lack functionality to manage product freshness, product expiry, shelf life and pricing of near-expiry products, which is crucial in grocery retail [5]. Limited privacy and data governance frameworks: Privacy concerns are talked about in many studies, but privacy compliant DT frameworks are still limited, particularly in real world data. Real-time DT synchronization latency: Most DT systems do not work in real-time. There can be differences between the digital model and real-life situation even when it comes to small delays. [6] Lack of common performance measures: Varied over the course of different studies, making it hard to compare across studies and fairly judge DT systems. It is the continued tradition of human civilization to have fifty different measurement systems for one problem [7].

C. Problem Statement

Retailers have multiple related issues when it comes to efficient inventory and supply chain management. The manual systems for inventory can be time-consuming, inaccurate, and do not offer up-to-the-minute information on available products on the shelves, resulting in stockouts, excess stock and losses. Furthermore, retailers face the challenge of determining the correct replenishment amounts and timings as the demand from customers fluctuates, the season changes and the supply becomes uncertain. It may also be hard to find products in the store if they are misplaced or improperly stored. Without automation, keeping the digital store environment accurate with constant updates can be a lot of work. In addition, grocery stores need to minimize food waste from overstocking fresh foods and enhance supply chain resilience in the face of other shocks, including pandemics, logistics failures, etc.

II. PERFORMANCE COMPARISON OF EXISTING DT METHODOLOGIES IN RETAIL GROCERY STORES

Here the current state of the art DT trends in retail grocery stores and inventory systems are compared.

A. Using Digital Twins to Create an Inventory Management System

In 2023, a combination of classical operations researches and the digital twin concept is used for inventory replenishment optimization in a manufacturing enterprise. The authors start with laying the theoretical groundwork for digital twins as virtual models that describe, predict and optimize physical processes with mathematical models. The main mathematical tool adopted is the well-known and easy-to-understand model that is known as the Economic Order Quantity (EOQ) model [7] and which is suitable in the context where the demand has known and relatively stable requirements. It calculates the optimum value of the order quantity Q_w that minimizes the cost of ordering the resource and storing the inventory of that resource in the form of raw materials: $Q_w = \sqrt{(2Kv/s)}$, where v is the intensity of the consumption of the resource (raw material) (quantity of resource consumed per unit time), K is the fixed order cost per delivery event or order, and s is the per-unit cost of inventory holding (raw material). The authors first perform a structured review of other inventory management methods, which guides the choice for using Wilson's model as the best formulation for the case study's stable and single resource consumption profile. The model by Wilson has clear assumptions, which are explicitly recorded: There are no restrictions on the external supply; the consumption intensity is constant and known, based on historical production data; the delivery time is the same for both orders and products; the product and the order are fulfilled in single batches; ordering costs do not depend on the size of the order; holding costs are proportional to the size of the order; there are no scope for planned shortages. Figure 1 shows the digital Twin–Integrated EOQ Workflow for Manufacturing Inventory Optimization. The four enterprise parameters are converted via the Wilson formula into four replenishment decisions, while a cost curve displays the relationship between replenishment frequency and holding costs at the calculated optimal replenishment lot size of 4.74 m².

B. Digital Twin in Retail-An AI-Driven Multi-Modal Approach for Real-Time Product Recognition and 3D Store Reconstruction

Proposed in 2024. Digital twin technology is a promising tool to tackle these operational requirements, sustainability challenges and resilience issues, by enabling monitoring, intelligent forecasting and scenario-based planning in real time. The pipeline consists of four stages of sequential processing: detection, recognition, tracking and spatial mapping, where each stage employs carefully chosen deep learning or signal processing methods and is tested on the smartphone platform for practical deployment. Stage 1 uses YOLOv8s (small variant of the 8th generation You Only Look Once architecture) for product detection in 2D images at the

speed of real time. It processes the video frames in a forward pass, creating the bounding boxes for the detected product regions. The small variant is chosen to optimize the speed of inference with the accuracy of detection, and is said to deliver a latency of just 7 milliseconds per frame on an iPhone 14 Pro Max. The detection stage is a one-class detector as it detects if a product is present in the package, as opposed to which product it is; hence, it is light and can be transferable among various product categories and packaging formats [9].

The second stage processes each cropped bounding box image using a Vision Transformer (ViT-base) model to make a fine-grained classification and assign the corresponding Global Trade Item Number (GTIN) to the identified product. The self-attention mechanism of the ViT model allows it to effectively extract long-range visual dependencies in the product image [10] which is crucial for distinguishing between visually similar products with differences in packaging details. The recognition model is learned from a dataset of 13,000 products, and paired product images are paired with the ground truth label comprising the barcoded GTIN. Inference time reported to be 8 milliseconds per crop which keeps the overall pipeline real time [11]. The third stage is to apply cross-frame tracking based on Euclidean distance between the centroid of the bounding boxes in two successive frames. This enables the camera to avoid any redundant recognition calls to the same product because of its movement, saving processing power and ensuring GTIN consistency over time. A result stability-locking mechanism complements

the tracker: If the GTIN is predicted to be the same in a number of the following frames, and the motion sensors are indicating that the camera is not moving, the result is determined as stable and entered into the digital twin update pipeline. Any results are discarded until the system becomes stable again [12]. The fourth and final stage combines the 2D to 3D coordinate mapping by projecting the position of the bounding box on the screen and using the depth data measured by the device's depth sensor, along with the spatial awareness data provided by the device's inertial measurement unit and Bluetooth/Wi-Fi positioning system. Each recognized product gets a 3D world coordinate in the store's global reference frame which fills the digital twin with location information that is correct in 3D space. The digital twin is used for two downstream applications: an AR overlay to verify shelf accuracy for staff, and an iOS AR wayfinding app that uses real-time 3D positioning to guide customers step-by-step to products on the shelves. The app was tested by 46 consumers and 23 retail employees to test the usability and satisfaction. In automated retail, AI is expected to play a pivotal role in the future of digital twin maintenance, as illustrated in Figure 2, which shows an AI Multi-Modal Processing Pipeline for Automated Retail Digital Twin Maintenance. The five-stage architecture starts with live smartphone video, followed by YOLOv8s detection, ViT based GTIN classification, stability locked 2D to 3D coordinate mapping, and real-time digital twin synchronization, before the AR powered customer wayfinding application.

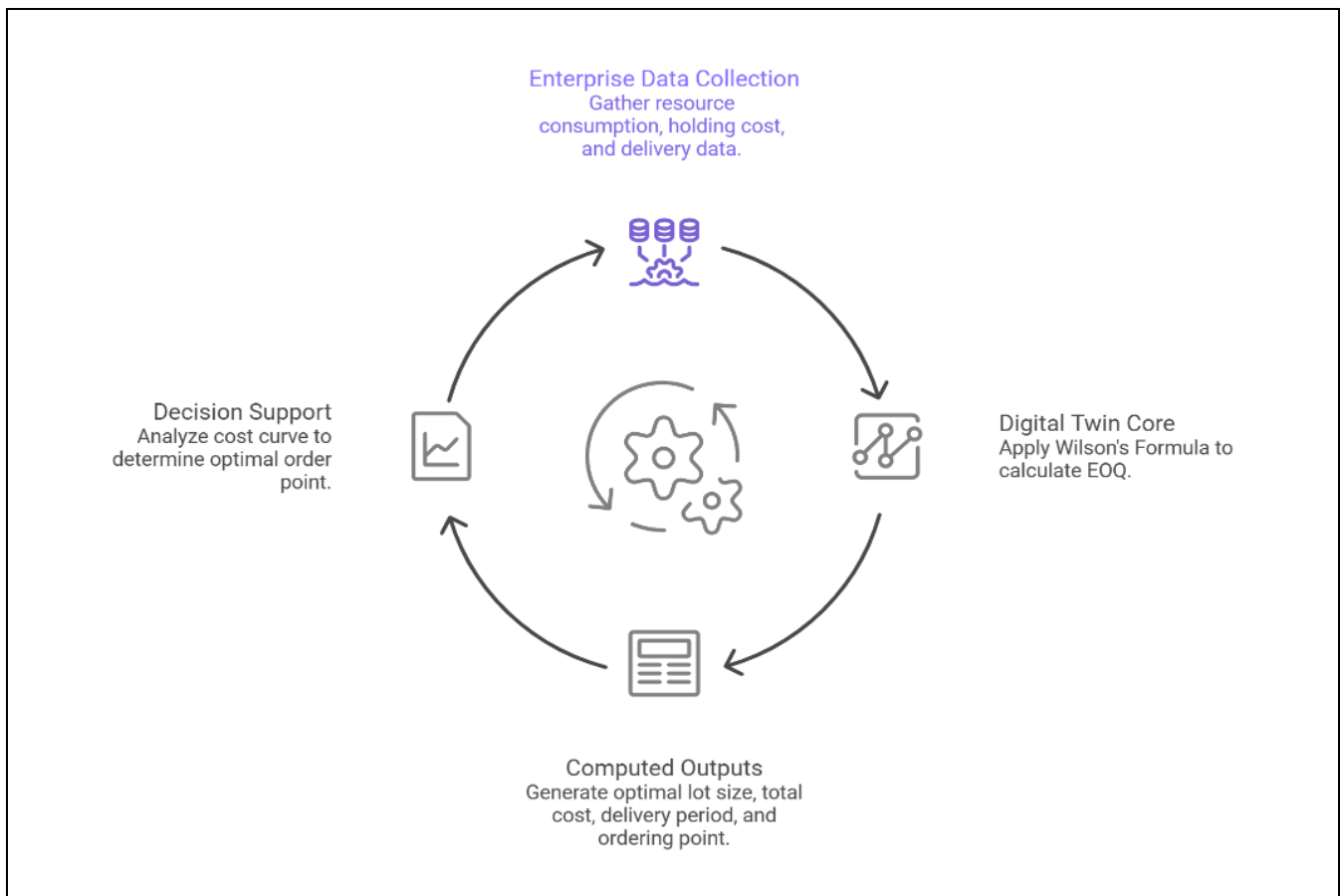


Figure 1: Wilson EOQ Integrated with Digital Twin

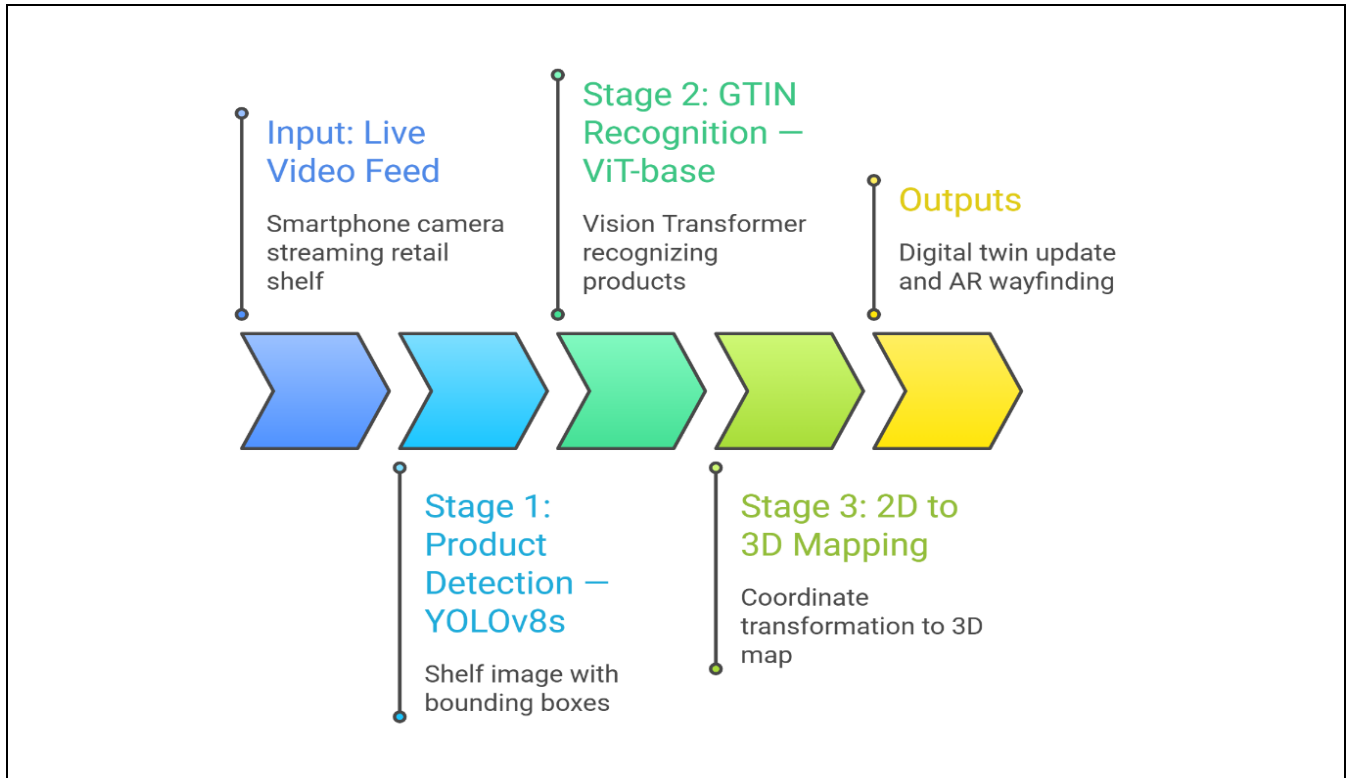


Figure 2: AI Driven Retail Digital Twin Creation Pipeline

C. Showing Products in a Retail Store Digital Twin with Item Location Captured by an RFID Robot

The article introduced a three-component system methodology that merges autonomous RFID scanning, catalogue data integration and photogrammetric 3D store modelling to create a populated, navigable digital twin of the retail store. The methodology is operationally practical and scalable, using commercially available hardware and software platforms instead of engineering solutions [13]. The first is the Keonn Technologies Robin200, an autonomous robot that uses optical and proximity sensors to navigate and keeps a track of the inventory. While the stores are closed to trading, Robin200 is programmed to complete inventory and location missions by moving along a set path in each aisle of the store and reading UHF RFID tags on every product along the way. The robot reads one tag every time it moves and stores the Electronic Product Code (EPC) identifier, as well as the estimated horizontal location (x, y) of the tag in the store's coordinate system based on its internal localization/modulation algorithms [14]. The location estimate of each SKU is the average position over all EPC reads during the mission where the read is associated with that SKU and thus the read-to-read positional noise is averaged out. If an EPC is simultaneously found in several different store locations, such as a promotional display and a regular store shelf, a clustering algorithm will divide the EPCs into separate groups based on the location and create a separate location entry for each group [15]. The ground truth inventory accuracy validation is obtained by conducting a detailed manual inventory count with a handheld RFID reader. The ground truth is the set of all tags detected by the handheld

reader or the robot and the inventory accuracy is the ratio of the number of ground truth tags detected by the robot only to the number of ground truth tags. Location accuracy is measured by manually measuring the exact x, y coordinates of $50 \times 5 = 250$ items across 5 departments, calculating the Euclidean distance between the robot estimated and manually measured locations, and calculating the average error for each department and the entire store [16]. The second is the product catalogue that provides the layer of enrichment to the raw SKU-location data that the robot consumes. For every SKU found, the system accesses the retailer's catalogue database to get the picture of the product, the text description and the current price. This enhanced dataset is the second content layer of the digital twin [17]. The third is a 3D digital model of the store created using the Matterport. There is a Matterport camera system installed throughout the store which takes high resolution photos at certain points and the Matterport website stitches them together into a 3D model. The RFID tag representations are written into this model by the coordinate estimates of the robot, Robin200, and the product catalogue data is enriched with this, which is attached to each tag position. The integrated system enables users to move around a 3D store model virtually and click on various sections of the model to get a real-time list of the stocked products with photos, descriptions and prices, demonstrating the functionality of a retail digital twin, comprising all of the commercial off-the-shelf components [18]. The overall architecture of the

RFID Robot and Matterport Digital Twin System is depicted in Figure 3.

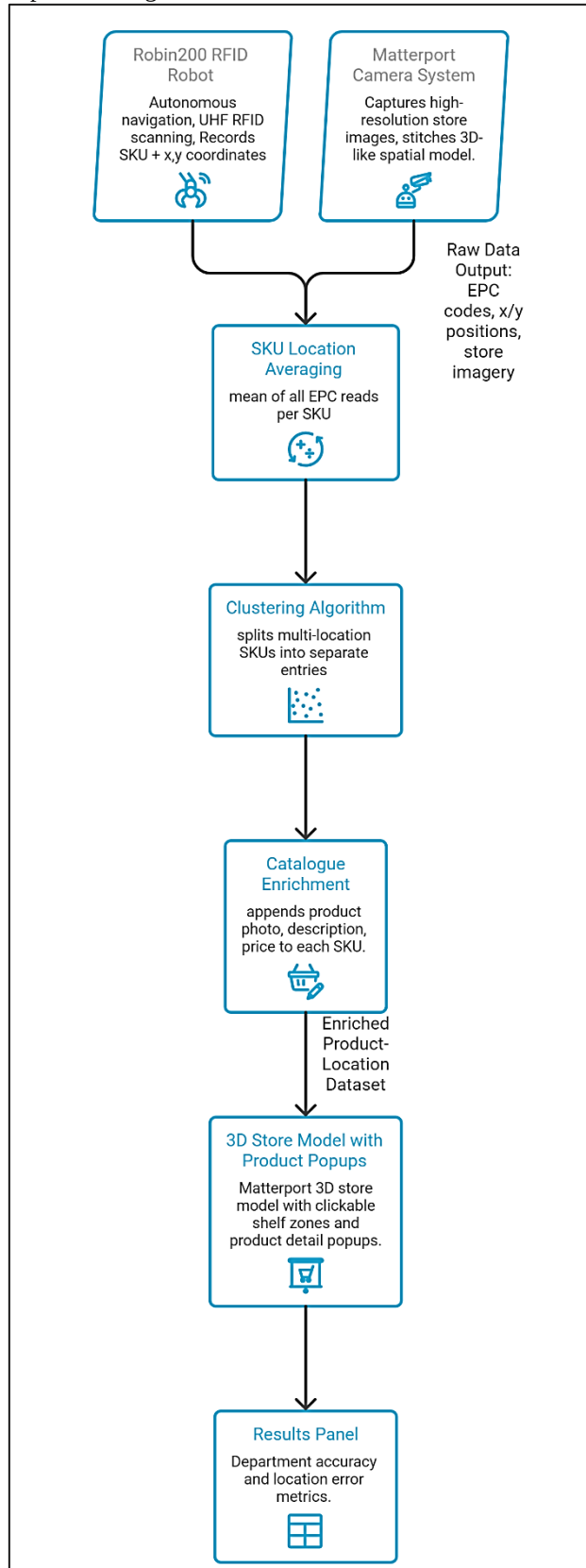


Figure 3: Retail Digital Twin Architecture Comprising the Robin200 RFID Robot, Matterport Camera System, and Integrated Data Processing Pipeline

D. Applying Digital Twins for Inventory Management and Retail Store Organisation

The article uses literature synthesis and conceptual framework development methodology which is carried out in five consecutive steps from theoretical basis to applied frameworks, the results of which are a conceptual framework. Instead of deploying and testing a technical system, the thesis framework an intellectually coherent blueprint for the implementation and deployment of digital twins in a supermarket setting, which is based on a detailed literature review of current definitions, classifications and case studies [19]. The first methodological step is a systematic analysis of the concept of digital twin. The thesis examines several scholarly definitions of DTs, and narrows those definitions down to the common components: a physical system, a digital system, and bidirectional data transfer, which allows for the two systems to be synced. Importantly, the methodology separates DTs from conceptually similar, but functionally different systems. Digital shadows are distinguished from complete DTs, with the latter allowing for physical to virtual and virtual to physical communication. The DT category does not include surrogate models, which are less expensive to evaluate than the expensive simulation. Similarly, simulation models are distinguished in that they operate on pre-made assumptions and are not based on continually updated real time data [20]. The digital thread concept, which is data architecture for continuity of information across the lifecycle, is presented as an additional tool for supporting DTs, not necessarily as a DT in itself. The second step is the classification of the digital twin according to the three dimensions: fidelity (partial, identical and augmented twins), scale (component, asset, system and process twins) and functionality (descriptive, analytical, diagnostic, predictive and prescriptive value levels). This taxonomy enables the thesis to align specific retail use cases, such as real-time shelf monitoring, demand forecasting and layout simulation to the relevant DT type and functional capability level, providing a structured foundation for the design of a framework. In the third step, the three main elements of a DT system (physical counterpart, digital counterpart, and data transaction layer) are identified and analyzed. This data transaction layer is explored in detail and the various types of data sources and streams are discussed: raw sensor data, pre-processed data streams, internal data sources (store systems, ERP) and external data sources (supplier feeds, market data). The thesis highlights the need for IoT connectivity to enable the real-time synchronization required to be able to distinguish between real time and static digital replicas (DTs) [21]. Case studies of Amazon Robotics (warehouse automation), Lowe's (layout and customer behavior optimization) and PepsiCo (distribution center workflow optimization) workplace implementations of retail DT are also explored, followed by technology product tours of RFID and AR systems. These cases contribute to an understanding of what has been put in practice and where there are gaps, especially when applied to supermarket specific needs. The fifth and final step puts together all

the analysis and proposes a supermarket DT framework, mapping operational challenges already identified through the analysis in inventory management (shelf-fullness detection, excess stock handling, book-vs-physical inventory reconciliation) and layout management (new product placement, layout error identification, AR visualization of changes) with the respective DT functionalities, and using the framework conceptually in an existing supermarket environment to show the expected

operational improvements. The H-DTCF applied to Supermarket Inventory and Layout Management is depicted in Figure 4. The framework helps to separate DTs from neighboring concepts, categorizes them according to the scope and function of the concept, and outlines their three core elements and their relation to supermarket operational challenges within layout and stock management.

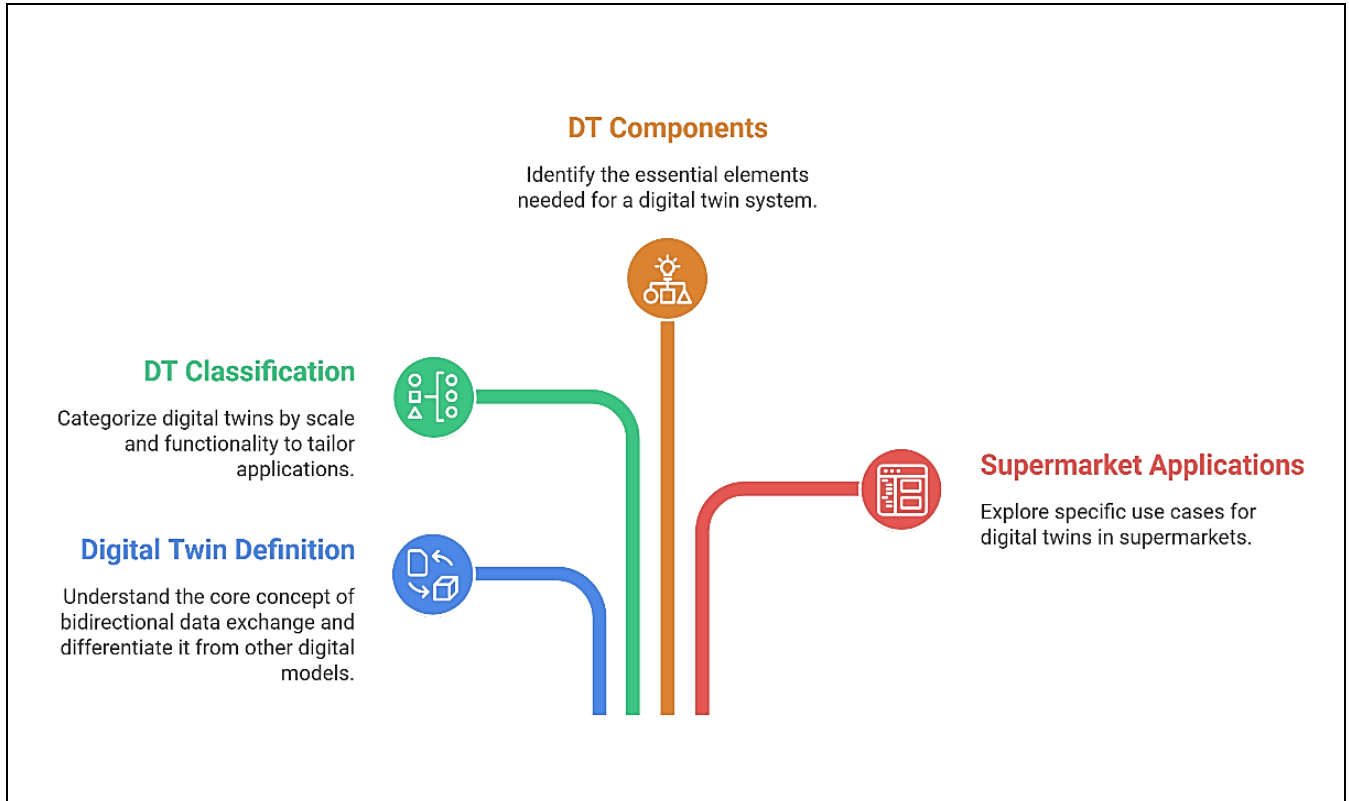


Figure 4: Hierarchical Digital Twin Classification Framework

E. A Digital Twin System for Retail Inventory & Sales Management

This approach involves the systematic literature review, conceptual architecture design, and functional prototype development and validation using simulated data in a three-phase research methodology. Each phase is a stepping stone to the next, starting with evidence synthesis, then architectural specification, and then technical implementation. The first phase performs a systematic literature review in IEEE Xplore and Science Direct databases using a set of Boolean strings that involve the terms ‘inventory management AND retail’, ‘RFID AND digital systems’ and ‘AI AND inventory management’ and applies a published period of 2015–2025. Only studies that do not concentrate on the production context or the supply chain, theoretical business models, non-English or inaccessible publications are screened out. Data extraction entails a structured matrix in Excel that represents the inventory system, method of use, technology, advantages, disadvantages and key findings described in each study. This synthesis gives rise to five different types of systems: manual systems, barcode systems, RFID systems, IoT and

sensor-based systems, and AI-supported systems. This comparative analysis inspires RFID with item-level tracking without line of sight and has the capability to incorporate AI analytics and motivate the proposed system. The second part designs a four-layer conceptual DT architecture. This store and warehouse layer aggregates and validates data from the RFID scanners and simulated POS events, stores the events locally in the event of a network failure, and sends authenticated events to the cloud through a Zero Trust Network Access gateway. The security and access layer provides Role Based Access Control (RBAC), mutual TLS 1.3 authentication, federated identity management through Azure/LDAP and a Security Information and Event Management (SIEM) system for ongoing audit logging that ensures GDPR compliance by only processing aggregated sales data, not individual records of customer behaviors. The corporate cloud layer brings together data from stores through an event bus (Apache Kafka or Google PubSub), schema registry, data lake and centralized AI analytics engine. The DT client layer is the part which offers 3D visualization and human-computer interaction. In the 3rd phase, a functional prototype is implemented and validated, employing 3D

visualization tools Unity (version 2022.3.62f1) and the client-server communication tool FastAPI (python 3.9). The data layer provides a SQLite driven store and warehouse stock simulation, with transaction like events from the point of sale (POS) causing the reduction of stock. The visualization is handled by four components: ProductSpawner associates 3D product prefabs with database product entities, ProductLabel uses current product stock status to traffic-light color code products in real-time, AnchorManager sets the transform of products to exact 3D shelf coordinates based on the positions in the current row of the products in the database, and the HeatMap subsystem overlays the product shelf sections with an intensity of color which relates to the sales

intensity of the products stored in that section. The demand forecasting is done by 3 models of AI namely Simple Moving Average, Weighted Moving Average, and Linear Regression with seasonal and holiday adjustment factors, which are then fed to an automated critical stock alert system that alerts to order, if it's deemed that demand is likely to exceed stock before a replenishment order is sent. Prototype validation takes place by functional demonstration on simulated data, end-to-end data flow, the responsiveness of the visualization and the action of the alert system are assessed, not the performance on live-store. Figure 5 shows Four-Layer Architecture of the Privacy-Conscious Retail Digital Twin Prototype.

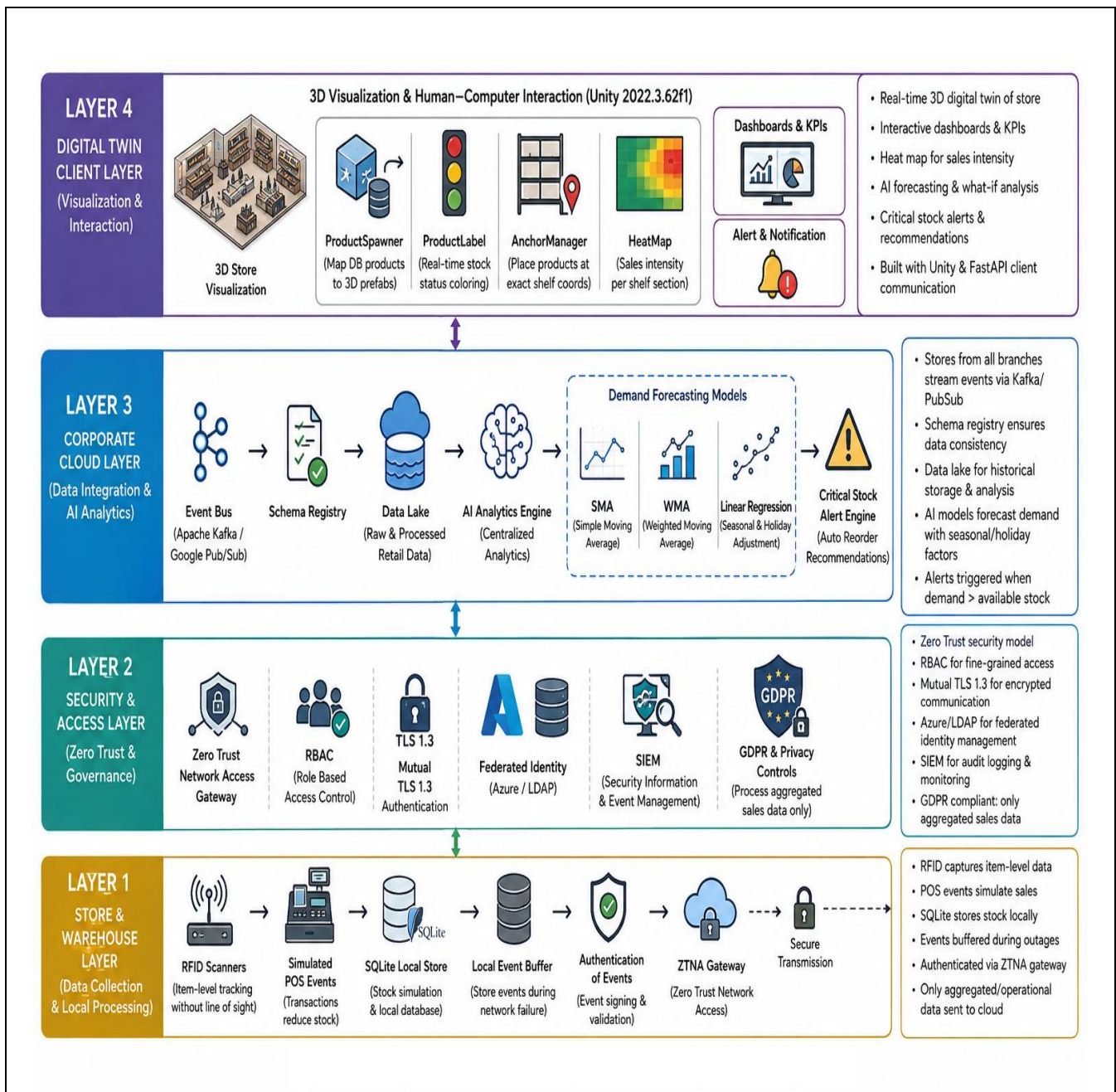


Figure 5: Four-Layer Architecture of the Privacy-Conscious Retail Digital Twin Prototype

F. Digital Twin of Retail Stores with RFID Tags Localization

In this Paper, a portable digital twin construction system is designed and validated, which combines probabilistic RFID tag localization and visual SLAM based 3D mapping. The methodology is based on three closely coupled technical subsystems: A Bayesian filter for the estimation of the RFID position, an RF fixed-transmission-power observation model, and RTAB-Map-based SLAM for reconstructing a 3D store based on observations. The system is realized using commercially available components: two Intel RealSense cameras and a handheld UHF RFID reader are installed on a portable scanning rig that is carried by the operator around the store. The Bayesian filter subsystem keeps track of a probabilistic belief distribution $B(x_t)$, which reveals the belief distribution over all the possible tag position in a discretized sensing area. The sensing area is subdivided into equally sized spatial grid cells, and the belief is modeled by a PMF over the cells. The filter follows two phases at every time step: prediction step – the belief is propagated forward in time based on a motion model, since the reader may have moved since the last RFID observation; update step – new RFID observations are used to update the belief. The update equation is $B(x_t) = \beta \cdot B(x_{t-1}) \cdot P(z_t | x_t, r_t)$; where β is a normalizing constant, z_t is the RFID observation at time t , and r_t is the position of the reader at time t . The estimated position for the final tag is the cell that has the highest belief on the grid - or the geometric average of cells that have the same belief.

G. Realizing Zero-Waste Value Chains through Digital Twin-Driven S&OP: A Case of Grocery Retail

This article uses a qualitative and interpretive research methodology based on the Gioia method for theory building from the case data and structured with the lens of resource orchestration theory. The approach is based on the duality of the research question: Grocery retail S&OP experts tend to be very knowledgeable about the technical aspects of DT, but not so much about the operational details of S&OP, and the opposite is also true. To connect these two knowledge worlds, the iterative, structured dialogue between a researcher and a practitioner, known as reflective conversation, is chosen as the core data collection technique, which integrates aspects of semi-structured interviews, expert elicitation and collaborative sense making. Case X is an integrated Norwegian grocery retailer and wholesaler, handling about 8,500 SKUs, with five product categories: dry goods, frozen, chilled, bread

and fruit and vegetables. The organization operates separate retailing and wholesaling business units, with the wholesaler responsible for inbound logistics, warehousing, and outbound distribution to stores, and the retailer unit managing assortment, supplier relationships, sales management, and store operations. This dual-structure creates planning complexity at the interface between the two units, making it a particularly relevant context for studying S&OP integration.

Primary data is collected through semi-structured interviews with four senior managers at Case X: a manager responsible for improvement and replenishment, a senior logistics project leader, a forecasting project manager, and a logistics development manager. These interviews are supplemented by secondary data from internal case documents, project reports, and published materials. Three reflective conversation sessions are additionally conducted with external participants: an S&OP consultant with cross-industry experience (referred to as SOX), a digital twin technology expert (DGX), and a solution provider group (SSP) actively developing DT-based supply chain planning tools.

Data analysis follows the Gioia methodology's three-stage coding process. First-order codes are derived directly from participants' language (in vivo coding), capturing the vocabulary and framings used by practitioners themselves rather than imposing external theoretical categories. These are aggregated into second-order themes through repeated comparison and abstraction, and finally synthesized into aggregate theoretical dimensions aligned with resource orchestration theory's three constructs: structuring (decisions about which resources and capabilities to accumulate, and how to design the DT model), bundling (combinations of resources and capabilities to construct new DT-enabled planning competencies), and leveraging (the operational deployment of bundled capabilities to achieve zero-waste outcomes through monitoring, scenario simulation, and intervention). The resulting framework is presented as a multi-level explanatory model of how grocery retailers can implement and derive value from DT-enabled S&OP for waste reduction, supported by illustrative quotations and case evidence from both the case company and external expert perspectives.

III. COMPARATIVE SUMMARY TABLE

Table I provides a structured comparison of all eight reviewed papers across five dimensions: paper title, methodology, research gaps resolved, key limitations, and applications addressed.

Table I: Comparative Analysis of State-Of-The-Art Digital Twin Systems for Retail Grocery Stores

Paper Title	Methodology	Research Gaps Resolved	Limitations	Applications Solved
Digital Twins for Inventory Management System	Wilson's EOQ mathematical model integrated with digital twin; data-driven parameterization from enterprise records	Optimizing replenishment decisions using formal mathematical models embedded in a digital twin framework	Assumes constant demand/delivery time; idealized no-shortage condition; single-item case study (pine boards only)	Manufacturing inventory optimization; optimal order size & timing; reduction of procurement costs

Paper Title	Methodology	Research Gaps Resolved	Limitations	Applications Solved
Digital Twin in Retail – AI-Driven Multi-Modal Approach	YOLOv8 product detection + Vision Transformer (ViT) GTIN classification + Euclidean tracking + depth-sensor 2D-to-3D mapping + AR overlay	Automating real-time product recognition and 3D shelf mapping to eliminate manual digital twin updates	Validated on single device (iPhone 14 Pro Max); GTIN dataset limited to 13,000 products; no multi-store generalization	Real-time shelf monitoring; AR product wayfinding for shoppers; automated store digital twin maintenance
Retail Store Digital Twin with RFID Robot	Keonn Robin200 RFID robot for autonomous scanning; Matterport 3D store digitization; average EPC clustering for SKU location estimation	Practical, scalable, automated inventory capture and item localization for full-store digital twin population	~0.92 m average location error; no vertical (z-axis) accuracy; limited to non-food sections; single-store experiment	Order picking route optimization; misplaced item detection; customer product guidance; inventory auditing
Applying Digital Twins for Inventory Management and Retail Store Organisation (BSc Thesis)	Literature-driven conceptual framework; DT type/component classification; AR visualization; case study mapping in real supermarket	Holistic DT framework addressing both layout management AND inventory management jointly for supermarkets	Conceptual only – no quantitative experiments or prototype implementation; findings not empirically validated	Supermarket layout optimization; shelf-fullness monitoring; excess stock management; AR-assisted store planning
A Digital Twin System for Retail Inventory & Sales Management (MSc Thesis)	Unity 3D visualization prototype + Python FastAPI backend + SQLite simulation + RFID/POS integration + SMA/WMA/LR demand forecasting models	Privacy-conscious (GDPR-aligned) real-time retail DT integrating AI forecasting with shelf monitoring	All data simulated (no live store validation); Unity prototype not production-ready; single-store simulation only	Shelf stock monitoring; demand forecasting; automated low-stock alerts; sales heatmap visualization; layout testing
Digital Twin of Retail Stores with RFID Tags Localization	Bayesian filter RFID localization using fixed RF transmission power model + RTAB-Map SLAM for 3D mapping + coordinate frame fusion	Robust RFID item localization under multipath interference integrated into a portable 3D digital twin scanner	Assumes stationary tags and line-of-sight; small testbed (33 tags); no large-scale real store validation; non-LOS conditions unhandled	Item-level localization in retail/warehouse; real-time inventory monitoring; misplaced item detection
Zero-Waste Value Chains through Digital Twin-Driven S&OP	Reflective conversation / qualitative case study (Gioia methodology); resource orchestration theory; senior manager interviews + external DT/S&OP expert conversations	Extending zero-defect manufacturing mindset to grocery retail via DT-enabled S&OP for proactive waste prevention	Single case (Norwegian grocery retailer); qualitative only; framework not quantitatively validated; DT not yet fully deployed	Food waste reduction; S&OP scenario planning; supplier network integration; demand-supply variability detection

IV. CONCLUSION

A digital twin has become a key part of the foundation of the next generation of Retail grocery store management systems. The review has shown that the applications of DT cover a wide spectrum of operational issues, including mathematical inventory optimization, shelf recognition by artificial intelligence, food waste reduction, and pandemic resilience planning, to name a few, and that in each of these domains, DT has delivered proven results in terms of efficiency, accuracy, or decision quality. As the COVID-19 pandemic has proven to be a significant real-world challenge, there is a growing interest in simulation-based DT approaches for supply chain resilience, as traditional planning tools have proven themselves to be inadequate. The studies reviewed here have demonstrated that discrete-event simulation models can be developed and calibrated to pandemic dynamics and can accurately simulate observed patterns of performance degradation, and identify what resilience strategies have the greatest impact, giving a valuable methodology to consider for the future for crisis preparedness. The key open challenges are to enable robust localization of items from sub-meter level in more

complex retail settings, to enable validated systems to be scaled from single-store to multi-store deployments, to enable digital twins to integrate at store level and supply chain level into a single planning framework, and to handle perishable items with all the temporal urgency they demand. To solve these problems, ongoing interdisciplinary cooperation between computer scientists, operations researchers, retailers and regulators will be needed. The economic argument for using digital twin technology in grocery retail will become much more compelling as sensor technology improves and the price of RFID tags, depth cameras and edge computing platforms continues to drop. The research described is a good foundation for that transition, both for practitioners and researchers.

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Authors Contributions

Afrahan Anwer: Literature search, data collection, analysis of relevant studies, and manuscript preparation. Muhammad Ovais Akhter: Conceptualization, supervision, critical review, and revision of the manuscript. Areeba Jawaid: Literature review, analysis of digital twin applications in retail, and manuscript drafting. Umair Akhter: Literature search, synthesis of findings, and manuscript editing. All authors contributed to the development of the manuscript, reviewed the final version, and approved it for publication.

Conflict of Interest

The authors declare no conflict of interest and confirm that this work is original and not plagiarized from any other source, i.e., electronic or print media. The information obtained from all of the sources is properly recognized and cited below.

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