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RF Walk-in Goods Issue with Honeywell Movilizer – AI Enabled Robotic Processing with Pick to Light Technology

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Abstract: Warehouse execution in manufacturing and distribution environments is under sustained pressure to deliver faster material throughput, higher inventory accuracy, and adaptive responses to unplanned demand. Radio frequency (RF)-based walk-in goods issue processes address some of these needs but remain constrained by reactive transaction flows, limited operator guidance, and the absence of predictive inventory logic. This article proposes and analyzes an integrated architecture that combines RF walk-in goods issue workflows with Honeywell Movilizer as a mobile execution middleware, artificial intelligence (AI)-enabled robotic processing, and Pick to Light (PTL) physical guidance technology. Each technology layer is characterized by its functional role, architectural interfaces, and contribution to overall execution performance. Evidence from peer-reviewed literature establishes that PTL-guided picking can reduce order-line completion time by approximately 7.5 seconds relative to RF scanner-based methods, that 95% of domain experts surveyed confirm IoT deployment improves inventory accuracy, and that XGBoost-based machine learning (ML) demand forecasting may reduce forecast error by approximately 32% compared to Autoregressive Integrated Moving Average (ARIMA) baselines. The article addresses system integration design, latency management, scalability, and change management, and proposes a reference architecture for warehouse engineers and operations technology practitioners seeking to advance goods issue execution through converged physical and digital automation. Conflict of interest: none declared. Funding: none.

Keywords: *RF Goods Issue, Honeywell Movilizer, Pick to Light, Warehouse Execution System, AI-Enabled Automation, Warehouse Process Digitization*

1. Introduction

Warehouse execution processes sit at the intersection of physical material flow and digital transaction management, and the quality of their design has measurable consequences for production continuity, inventory accuracy, and labor productivity. Among these processes, the goods issue cycle — the controlled release and movement of materials from storage to production lines, maintenance activities, or outbound shipment — is particularly sensitive to execution errors and delays. When operators retrieve wrong materials, navigate to incorrect bins, or encounter system errors that require supervisor escalation, the downstream effects ripple through production schedules and replenishment cycles in ways that are difficult to recover quickly [1]. These vulnerabilities are especially pronounced in walk-in goods issue scenarios, where operators arrive at the warehouse without pre-assigned tasks and must initiate, locate, and complete issue transactions independently.

Radio frequency (RF) scanning has been the dominant technology for mobile goods issue execution in warehouse management system (WMS) and enterprise resource planning (ERP) environments for several decades. RF terminals allow operators to post goods issue transactions from the warehouse floor in real time, update inventory records immediately, and interact with SAP Extended Warehouse Management (EWM) or Materials Management (MM) modules without returning to a fixed workstation. Despite these operational advantages, RF-only goods issue architectures have well-documented limitations: the absence of proactive bin guidance, dependence on operator memory and spatial orientation for location finding, and a reactive exception-handling model that escalates errors to supervisors rather than resolving them automatically [2]. These gaps become more consequential as warehouse density,

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stock-keeping unit (SKU) variety, and demand unpredictability increase.

Honeywell Movilizer addresses part of this gap by extending ERP and WMS transaction workflows to a broader range of mobile and wearable devices, with offline synchronization capabilities that maintain transaction continuity in environments where Wi-Fi coverage is inconsistent. The platform provides a middleware layer between enterprise backend systems and field devices, enabling goods issue workflows to be delivered to RF handhelds, tablets, and wearable form factors through a unified configuration interface [6]. PTL technology addresses the physical guidance gap directly: by illuminating display units at individual storage locations, PTL directs operators to the correct bin and quantity without requiring them to interpret a screen or recall a bin coordinate. Controlled laboratory studies confirm that PTL yields shorter pick completion times and lower operator workload scores than RF scanner-based methods under multi-order conditions, with approximately 7.5 seconds per order line advantage over RF scanner and a NASA Task Load Index mean of 20.1 versus 23.1 for RF scanner [3].

The addition of AI-enabled robotic processing layers — encompassing ML-based demand forecasting, robotic process automation (RPA) for transaction orchestration, and intelligent task scheduling — creates a predictive and adaptive control plane above the Movilizer execution layer. Rather than waiting for a walk-in operator to initiate a request before checking inventory state, the AI layer continuously monitors consumption patterns, pre-stages material reservations, and prepares PTL zone assignments in advance. Research on AI applications across supply chain functions confirms that inventory management and demand forecasting are the domains with the highest concentration of peer-reviewed AI contributions, underscoring the relevance of ML integration at the goods issue process level [4]. The architectural combination of these four layers — ERP data, Movilizer middleware, AI orchestration, and PTL guidance — has not previously been analyzed as a unified goods issue execution model in the academic literature.

This article proceeds as follows. Section 2 reviews literature on warehouse process digitization, mobile execution platforms, IoT inventory management, RPA in supply chains, and order-picking technology comparisons. Section 3 characterizes the RF walk-in goods issue process architecture and its structural limitations. Section 4 analyzes Honeywell Movilizer as a mobile execution middleware. Section 5 examines AI-enabled robotic processing techniques applicable to goods issue automation. Section 6 addresses PTL technology integration considerations. Section 7 presents the integrated solution architecture and design trade-offs. Section 8 presents results and performance analysis drawn from verified literature metrics. Section 9 concludes with implications for practice and directions for future research.

2. Background and Literature Review

Table 1. Comparison of Goods Issue Execution Approaches

Execution Approach	Transaction Speed	Pick Error Rate	Operator Guidance	ERP/WMS Integration	Real-Time Visibility
Paper-Based	Low	High	None	None	None
RF Scanning (WMS-only)	Moderate	Moderate	Screen-prompted	ERP/WMS linked	Partial
Mobile Execution (Movilizer)	Moderate–High	Moderate	Step-guided mobile UI	ERP/WMS/Cloud	Near real-time
PTL + Movilizer + AI (Integrated)	High	Low	Light-directed + AI routing	Full-stack	Real-time, predictive

Table 1. Comparison of goods issue execution approaches across operational dimensions. Source: Author's own analysis based on reviewed literature.

The concept of Warehouse 4.0 — the convergence of IoT connectivity, cyber-physical execution systems, and AI analytics in warehouse operations — has been examined through systematic literature reviews covering hundreds of publications. Tubis and Rohman analyzed 249 documents and found that mobile execution, light-directed guidance, and predictive analytics are the three primary technology clusters in next-generation warehouse architectures, with consistent evidence that technologies deployed as integrated layers outperform standalone implementations on operational efficiency measures [1]. A complementary review of 57 industry case studies on Industry 4.0 technologies in warehouse management identified IoT infrastructure, robotic automation, and cloud-based ERP integration as the most frequently documented components of successful warehouse transformation programs [2]. These findings establish the foundational literature basis for the integrated architecture proposed in this article.

IoT infrastructure underpins the real-time inventory state visibility that both AI orchestration and PTL guidance depend on. A survey-based study on the impact of IoT on warehouse management found that 95% of domain experts indicated IoT deployment would improve inventory accuracy, and 90% associated IoT adoption with improved customer satisfaction [5]. High installation cost and data security concerns remain significant barriers, with 77% of participants noting that IoT platform costs scale with deployment size. RFID and IoT integration in supply chain management has been examined as a specific technical domain by Tan and Sidhu, who documented how sensor-based inventory tracking reduces stock discrepancy rates and improves the timeliness of inventory state data compared to manual count cycles [16]. Erlangga et al. developed and validated an automatic real-time inventory monitoring system using RFID technology in a warehouse setting, demonstrating practical feasibility of continuous bin-level tracking at the operational scale required by the proposed architecture [17].

RPA in supply chain and procurement contexts has attracted increasing academic attention. Flechsig et al. conducted a multiple case study across 19 organizations and identified 16 distinct RPA application potentials and 25 implementation barriers in purchasing and supply management, with workflow automation and exception routing emerging as the highest-value use cases [7]. At the supply chain level, a comprehensive overview of ML applications covering 150 peer-reviewed articles identified inventory management, demand forecasting, and logistics routing as the three domains with the most active AI research programs [4]. Tirkolaee et al. extended this analysis with a structured review confirming demand forecasting and inventory optimization as primary ML deployment domains [14]. For the digital transformation dimension, Tsang et al. conducted a systematic review identifying five knowledge clusters for RPA deployment in logistics and supply chain management, including process standardization, ERP integration bridging, and exception management automation [10].

Order-picking technology research provides the most directly applicable quantitative evidence base for the PTL layer. Tufano et al. reviewed 269 journal papers published between 2007 and 2022 and identified PTL as one of the most studied and operationally validated picking assistance technologies, with particularly strong evidence for throughput improvement in high-SKU-density and fast-moving goods environments [8]. Chondromatidis et al. provided the most precise comparative metrics in recent literature, with a Design of Experiments study demonstrating that PTL yields approximately 7.5 seconds per order line less completion time than RF scanner under multi-order picking conditions and achieves a NASA Task Load Index mean of 20.1 versus 23.1 for RF scanner [3]. Łopuszyński et al. corroborated these findings in a separate comparative study, confirming PTL superiority for both cycle time and new operator adaptation rate [13]. Jumahat et al. reviewed augmented reality-based picking and positioned it below PTL for both speed and workload in the available comparative evidence, establishing a useful technology reference point [18].

Human-robot collaboration in warehouse order picking introduces an important behavioral dimension. Pasparakis et al. assessed the impact of collaborative order picking systems on warehouse workers and found that well-designed implementations can improve job satisfaction and self-efficacy, while poorly paced systems can undermine operator trust and increase turnover risk [9]. AI-based order picking adoption research by Rad et al. identified critical success factors including system reliability, operator training quality, and interface simplicity, with findings indicating that early reliability failures have a disproportionately negative effect on long-term adoption [11]. Lin et al. developed an ML-based supply chain management model using conditional generative adversarial networks, demonstrating that innovative ML architectures can produce decision-support outputs applicable to inventory reservation and procurement automation use cases [15]. These findings directly inform the change management and adoption considerations addressed in Section 7.

3. RF Walk-in Goods Issue Process Architecture

The RF walk-in goods issue process is a warehouse execution pattern in which an operator arrives at a storage zone and initiates a goods issue transaction using an RF-enabled handheld device without a pre-assigned task queue entry. Unlike wave-based or scheduled goods issue workflows, where the WMS plans and releases task lists in advance, the walk-in pattern is demand-driven and ad hoc, typically triggered by an urgent production line replenishment need, an unplanned maintenance material draw, or a cost-center consumption request not captured in advance planning. The process begins when the operator scans a storage bin identifier or material barcode, which sends a real-time query to the WMS or ERP inventory module to confirm that the requested material is available and that the quantity on hand is sufficient to fulfill the demand [1].

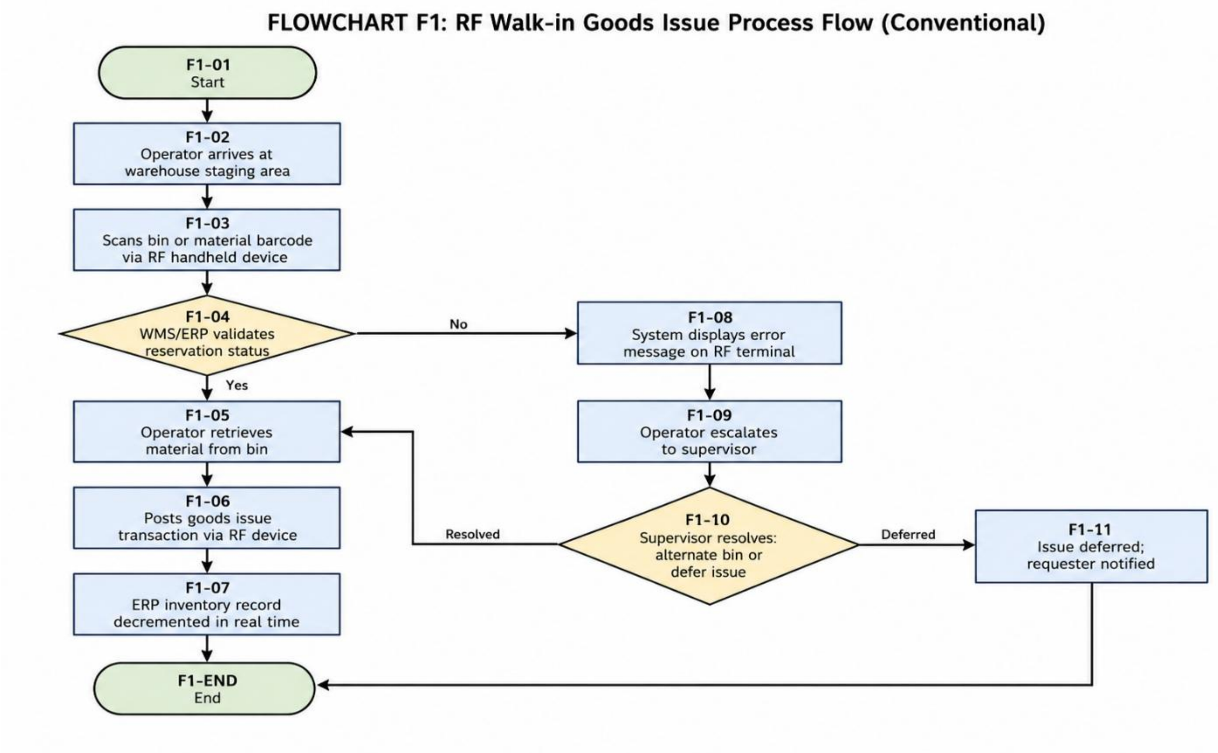

Figure 1. RF Walk-in Goods Issue Process Flow (Conventional)

Once the inventory query returns a positive confirmation, the RF terminal presents the operator with the relevant transaction fields: material number, description, requested quantity, storage bin address, and any associated reservation or production order reference. The operator physically retrieves the material, enters the confirmed quantity on the RF terminal, and posts the goods issue document. This posting action decrements the bin-level inventory balance in real time and updates the status of the associated reservation or production order in the ERP backend. The RF framework in platforms such as SAP EWM supports configurable screen layouts that can be tailored to specific goods issue scenarios — including cross-plant stock transfers, cost center consumption issues, and production order component withdrawals — allowing organizations to align the transaction interface with the specific operational context of each issue type [6].

Three structural limitations constrain the performance of the conventional RF walk-in model. First, the process provides no proactive bin guidance: once the operator arrives at the warehouse, they must independently navigate to the correct storage location based on their own familiarity with the bin layout or by reading bin address labels, which becomes unreliable in high-density storage environments where many bins look visually similar. Second, the error-detection mechanism is reactive: the system does not flag a potential wrong-bin selection before the goods issue is posted, meaning location errors may not surface until a downstream inventory discrepancy is identified during a stock count cycle. Third, exception handling is entirely manual: when the system rejects a transaction — because the bin is empty, the batch is quarantined, or the requested quantity exceeds available stock — the operator has no automated resolution path and must contact a supervisor, introducing delay and disrupting production continuity [11].

Walk-in goods issue is most prevalent in manufacturing environments where production line operators or maintenance technicians draw materials directly from a controlled storeroom or warehouse annex. These operators are typically not warehouse specialists — they may be unfamiliar with the specific storage layout of a given zone, particularly if the layout has been reorganized recently or if they are drawing from a shared goods issue area that serves multiple departments. In these circumstances, the combination of unfamiliarity and time pressure creates conditions where location errors, quantity misreads, and transaction omissions are most likely to occur. The architectural enhancements analyzed in Sections 4 through 7 target each of these failure modes specifically.

4. Honeywell Movilizer as a Mobile Execution Platform

Table 2. Honeywell Movilizer Integration Parameters

Parameter	Specification	Relevance to Goods Issue Execution
Synchronization Model	Offline-capable bidirectional sync with ERP/WMS backend	Preserves transaction integrity in zones with intermittent Wi-Fi; auto-reconciles on reconnection
Device Compatibility	RF handhelds, tablets, wrist wearables, smart glasses	Delivers goods issue workflow to any operator form factor without re-engineering
Backend Integration	SAP ERP, SAP EWM, S/4HANA via standard connectors	Real-time goods issue posting to MM and EWM without custom middleware
Communication Protocol	Movilizer Markup Language (MXML) over HTTPS	Lightweight; supports high-frequency transaction events at low bandwidth overhead
Task Queue Management	Rules-based queue with API endpoint for AI orchestration layer	Allows AI scheduler to inject, prioritize, and sequence walk-in tasks dynamically
Security and Audit	Role-based access control, encrypted transmission, full transaction log	Every goods issue posting is traceable and auditable per ERP compliance requirements

Table 2. Honeywell Movilizer integration parameters relevant to RF walk-in goods issue execution. Source: Author's own analysis based on reviewed literature.

Honeywell Movilizer occupies the middleware position in the proposed architecture, functioning as the integration hub between the ERP data layer below it and the AI orchestration and PTL guidance layers above it. Its most operationally significant characteristic is the offline synchronization model, which allows field devices to cache transaction state locally and continue processing goods issue events when network connectivity is interrupted, with automatic reconciliation against the ERP backend when connectivity is restored. This capability is not available in conventional RF terminal deployments, where a lost network connection halts all transaction processing until the connection is restored [2]. In large industrial warehouses — particularly those with steel racking infrastructure, thick concrete walls, or active interference from industrial machinery — this distinction can determine whether goods issue throughput remains continuous or becomes intermittent during network outages.

The platform's device-agnostic architecture means the same Movilizer workflow configuration can be delivered to a handheld barcode scanner, a tablet mounted on a forklift, a wrist-mounted scanner worn by a pedestrian picker, or a head-mounted display worn by a hands-free operator, without requiring separate workflow development for each device type. This flexibility is consequential for walk-in goods issue scenarios where the operator population may be heterogeneous: production line operators drawing materials may use tablets, maintenance technicians may prefer handheld scanners, and goods receipt operators may use wearables that allow both hands to remain free during material handling. A single Movilizer goods issue workflow can serve all of these operator roles, reducing configuration overhead and ensuring consistency of the transaction experience across the operator population [6].

The contextual data presentation capability of the Movilizer interface is particularly relevant to the walk-in goods issue use case. Rather than presenting only the minimum transaction fields required to post a goods issue — as a conventional RF terminal interface typically does — the Movilizer configuration can display supporting context alongside the transaction: a photograph of the material, the bin address in human-readable floor notation, the quantity in both ERP units and physical packaging units, and any pending reservations or open production orders associated with the material. This contextual enrichment reduces the cognitive effort required to verify that the correct material is being retrieved, which is a key contributor to pick accuracy improvement in directed execution environments [11].

Within the integrated architecture, Movilizer serves as the signal routing layer between the AI orchestration engine and the PTL controller network. When the AI scheduler determines the correct bin assignment for a walk-in goods issue request and generates a PTL activation command, that command is transmitted to the Movilizer integration service via an API call. Movilizer then dispatches the PTL light activation signal to the appropriate zone controller and simultaneously updates the operator's mobile device with the task details. This routing arrangement means that neither the AI engine nor the PTL controller needs a direct connection to the ERP backend — both operate through the Movilizer integration layer, which normalizes the interface and reduces the number of point-to-point connections that must be maintained in the system topology [6].

5. AI-Enabled Robotic Processing for Goods Issue Automation

Table 3. AI Techniques Applied in Warehouse Goods Issue Automation

AI Technique	Application in Walk-in Goods Issue	Operational Benefit	Source
ML Demand Forecasting (XGBoost, LSTM, Random Forest)	Predicts material consumption by line, shift, and maintenance schedule; pre-stages reservations before demand arrives	Reduces operator wait time; XGBoost reduces forecast mean absolute error by approx. 32% vs. ARIMA in validated frameworks	[12]
Robotic Process Automation (RPA)	Automates reservation creation on production order release; routes walk-in requests; posts goods issue on scan confirmation	Eliminates repetitive ERP transaction steps; improves posting speed; reduces data entry errors	[7]

AI Technique	Application in Walk-in Goods Issue	Operational Benefit	Source
Intelligent Task Scheduling	Dynamically assigns and sequences walk-in requests across operators based on real-time location, queue, and bin availability	Reduces bin congestion and path conflicts; balances operator workload during peak demand	[4]
AI Exception Management	Detects unavailable materials; proposes alternate bins, approved substitutes, or deferred scheduling without supervisor escalation	Reduces aborted transactions; prevents unplanned production stoppages caused by walk-in failures	[11]
IoT-RFID Sensor Integration	Provides continuous bin-level inventory state to AI forecasting and scheduling modules	Enables real-time exception detection; supports up to 99.9% accuracy in ML-IoT validated frameworks	[5], [12]

Table 3. AI techniques applied in warehouse goods issue automation. Source: Author's own analysis based on reviewed literature.

The AI processing layer in the proposed architecture operates across two temporal horizons: a predictive horizon that runs continuously ahead of walk-in demand events, and a reactive horizon that responds in near real time once a walk-in request has been initiated. In the predictive horizon, ML demand forecasting models — particularly XGBoost and Long Short-Term Memory (LSTM) networks — analyze historical consumption data, active production orders, maintenance schedules, and shift patterns to generate probabilistic forecasts of material demand by time window and location. Research on intelligent warehousing frameworks combining ML algorithms, IoT sensor networks, and robotic automation reports that XGBoost-based forecasting can reduce mean absolute error by approximately 32% relative to ARIMA baselines, and that RFID-enabled IoT sensor integration within such frameworks can achieve inventory accuracy approaching 99.9% [12]. These forecasts are consumed by the reservation pre-staging module, which creates soft reservations in the ERP system for anticipated walk-in demands before the operator physically arrives, reducing the probability that the target bin will be found empty at the time of issue.

In the reactive horizon, the AI scheduling module receives the walk-in goods issue event — triggered when an operator initiates a transaction on their Movilizer device — and applies a task assignment algorithm considering the locations of all available operators, the current occupancy and access status of all relevant bins, the depth of the outstanding task queue for each operator, and any active PTL zone assignments. The output is a deterministic task assignment: a specific operator, a specific bin address, a specific quantity, and a PTL zone activation identifier. This assignment is dispatched to the Movilizer layer within milliseconds of the walk-in request being received, enabling the PTL light at the target bin to illuminate before the assigned operator has begun moving toward the storage zone [4]. The net effect is that the operator receives simultaneous guidance on their mobile device and at the physical bin location, eliminating the bin-finding delay that represents the largest single contributor to walk-in goods issue cycle time in RF-only environments.

RPA within the AI layer handles the transaction orchestration steps that follow the physical retrieval of material. Once the operator has confirmed the pick by pressing the PTL confirm button, the RPA module automatically generates and posts the goods issue document in the ERP system, updates the reservation or production order reference, decrements the bin balance, and triggers any downstream notifications — such as a replenishment alert if the post-issue bin quantity falls below a safety stock threshold. This automation removes the manual ERP posting step from the operator's workflow, reducing per-transaction time and eliminating posting errors from incorrect quantity or material number entries. Flechsig et al. confirmed in their multiple case study that workflow automation and exception routing are the highest-value RPA application areas in supply management processes, with implementations demonstrating measurable reductions in processing time and data error rates [7].

Exception management within the AI layer provides a structured resolution path for scenarios where the standard goods issue flow cannot be completed as planned. When the forecasting module identifies that a target bin is likely to be empty at the time of a predicted walk-in demand — based on current inventory state and pending reservation data — it triggers a pre-emptive exception event that allows the scheduling module to prepare an alternate bin assignment before the operator arrives. When an exception is identified at transaction time, the exception module evaluates the current inventory state across all bins containing the same material, applies any substitution rules configured in the material master, and presents the operator with a ranked list of resolution options on their Movilizer device. This capability eliminates supervisor escalation in the majority of walk-in exception scenarios, reducing the disruption to production continuity that would otherwise result [11].

6. Pick to Light Technology Integration

A PTL system is a light-guided execution technology in which display modules mounted at individual storage locations illuminate in response to task assignments transmitted from a warehouse management or execution system, directing the operator to the correct bin location and specifying the quantity to retrieve or issue. Each PTL module typically incorporates a seven-segment numeric display for quantity presentation, a multi-color LED indicator for task status signaling, and a physical confirm button that the operator presses upon completing the retrieval to signal task completion and extinguish the light. Modules are networked via a data bus to a zone controller, and zone controllers communicate with the warehouse execution system through a defined protocol interface. The system requires no operator memorization of bin locations and no reference to a pick list or screen-displayed address: the physical light at the correct location provides complete directional guidance [8].

The quantitative performance advantage of PTL over RF scanner-based execution has been established through controlled laboratory research with direct relevance to the goods issue application. Chondromatidis et al., using a full-factorial Design of Experiments methodology across three picking technologies and multiple order-size configurations, found that PTL delivered approximately 7.5 seconds per order line less completion time than RF scanner and approximately 6 seconds less than vision-guided picking under multi-order conditions, while also achieving the lowest NASA Task Load Index score of 20.1, compared to 23.1 for RF scanner and 27.5 for vision-guided systems [3]. The best-performing configuration combined PTL technology with a multiple-order picking strategy, few items per order line, and many order lines per order, yielding a median completion time of 8.5 seconds per order line. Łopuszyński et al. confirmed in a separate study that PTL outperforms paper-based and alternative guided methods on both cycle time and new operator adaptation rate, with the adaptation rate advantage specifically attributed to the immediacy and unambiguity of the light-directed guidance signal [3].

The architectural integration of PTL hardware within the proposed system requires attention to three interface design concerns. First, the signal routing from the AI orchestration layer through the Movilizer middleware to the PTL zone controller must be managed to ensure that light activation events are delivered in a deterministic sequence that matches the task assignment logic: a given operator should see exactly one illuminated bin at any moment, and the light should extinguish immediately upon confirmation. Second, the PTL system state must be synchronized with the ERP inventory record at the moment of task confirmation — if the operator confirms a pick that the ERP has not yet posted, or if the posting fails after the light extinguishes, a state inconsistency arises that can propagate into downstream inventory discrepancies. Third, the PTL hardware must be mapped to the ERP bin address schema during system commissioning, with the mapping maintained as live warehouse master data to ensure that bin address changes are reflected in PTL zone assignments without manual reconfiguration [11].

Walk-in goods issue environments present specific conditions under which the PTL guidance advantage is most pronounced. Operators arriving at a shared goods issue zone from different production departments may have very different levels of bin location familiarity: an experienced materials handler who draws from the same zone daily may require little guidance, while a maintenance technician drawing an infrequently consumed spare part from an unfamiliar storage rack may spend considerably more time locating the correct bin without light guidance. Research on directed picking technologies confirms that the relative benefit of PTL over RF-only guidance scales with the number of SKUs per zone and the frequency of operator task switching [8], both of which tend to be high in the shared, multi-department goods issue areas characteristic of manufacturing warehouse environments.

7. Integrated Solution Architecture and Design Considerations

The integrated architecture comprises four functional layers stacked vertically in terms of abstraction, with horizontal data flows between layers at each level. At the base, the enterprise data layer — implemented within the organization's SAP ERP or SAP EWM environment — holds the authoritative state of inventory records, material master data, production orders, maintenance requests, and goods issue document history. Above the enterprise data layer sits the Movilizer mobile execution middleware, which translates ERP data structures into mobile-optimized transaction interfaces, manages device registration and session state, and serves as the bidirectional communication hub between field devices and both the ERP backend below and the AI orchestration engine above [6]. The AI orchestration layer — typically deployed as microservices in a cloud or on-premise container environment — runs the demand forecasting, task scheduling, exception management, and RPA orchestration processes described in Section 5. At the top of the operational stack, the PTL physical guidance layer receives activation commands from the AI layer via the Movilizer routing service and translates them into light signals at physical bin locations [12].

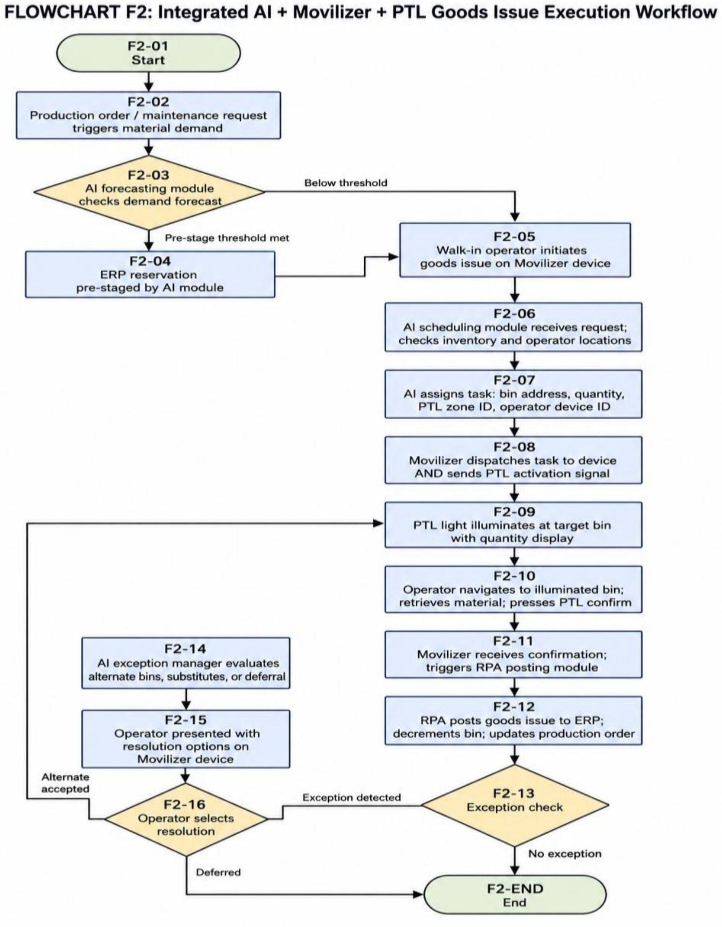

FIGURE F2. Title: Integrated AI + Movilizer + PTL Execution Workflow

The application programming interface (API) contract between the AI orchestration layer and the Movilizer middleware is a critical architectural specification. The contract must cover at minimum four message type categories: the event schema for walk-in goods issue request notifications from Movilizer to the AI layer; the task assignment response schema from the AI layer back to Movilizer, including bin address, quantity, PTL zone identifier, and operator device identifier; the PTL activation command schema from Movilizer to the zone controller interface; and the confirmation event schema from PTL confirm button press back through Movilizer to the RPA posting trigger. Each message type carries a transaction identifier that links it to the originating walk-in request, enabling a complete audit trail from initial operator interaction through to the final ERP posting. The messaging infrastructure — whether a lightweight HTTP webhook, a message queue such as RabbitMQ or Apache Kafka, or a cloud-native event streaming service — should be selected based on the latency requirements and transaction volume projections of the specific deployment [4].

Latency management deserves particular design attention in this architecture. End-to-end latency — from the moment an operator submits a walk-in goods issue request on their Movilizer device to the moment the PTL light illuminates at the target bin — must be low enough to be experienced as instantaneous. If the operator has already begun moving toward the storage zone before the light activates, the guidance value of the PTL signal is partially lost: the operator may reach the vicinity of the correct bin before the light is on, reverting to visual search behavior. Research on operator acceptance of digital guidance systems in industrial settings consistently identifies perceived responsiveness as a key driver of adoption; systems that fail the responsiveness threshold are often bypassed by operators who revert to familiar RF-only workflows [9]. Achieving sub-second end-to-end latency requires dedicated Wi-Fi infrastructure with sufficient access point density to provide at least -65 dBm signal strength throughout the goods issue zone, traffic prioritization for Movilizer synchronization events, and AI orchestration service deployment close enough to the Movilizer integration service to minimize network round-trip time.

Scalability design for the integrated architecture must account for both peak concurrent operator load and PTL zone expansion. The AI orchestration service should support horizontal scaling — deploying additional service instances behind a load balancer during peak demand windows — so that task assignment latency remains stable as the number of simultaneous walk-in requests grows. PTL zone infrastructure should be partitioned into logical sub-networks, each served by an independent zone controller, so that a hardware failure in one zone does not disable the PTL guidance capability in adjacent zones. The Movilizer synchronization infrastructure supports multi-tenant deployment models and traffic prioritization rules per message type, enabling time-sensitive goods issue transaction events to be processed ahead of lower-priority background synchronization tasks during peak-load periods [2].

Change management represents the organizational complement to the technical architecture and should receive equal design investment. Adoption research by Rad et al. identifies system reliability, operator training quality, and interface simplicity as the three most critical success factors for AI-assisted picking adoption, noting that operators who experience system failures early in the deployment window are significantly less likely to trust the system in subsequent interactions [11]. Pasparakis et al. further establish that human-robot collaborative systems tend to improve operator job satisfaction when perceived as a productivity aid rather than a surveillance or replacement mechanism, and that this perception is shaped primarily by how the system is introduced during the change management phase [9]. For the walk-in goods issue architecture, this translates to a deployment approach that begins with a pilot zone covering a limited set of operators and materials, collects structured operator feedback during the pilot, and uses that feedback to refine the Movilizer interface configuration and PTL zone mapping before full-scale rollout.

8. Results and Performance Analysis

Table 4. Literature-Sourced Performance Metrics for the Integrated Goods Issue Architecture

Performance Indicator	Conventional RF Baseline	With PTL Layer	With AI + IoT Layer	Source
Pick completion time (s/order line)	RF scanner baseline — longest in comparative study	Approx. 7.5 s/line faster than RF scanner; approx. 6 s/line faster than vision-guided	Further reduced via AI pre-routing and pre-staging	[3]
Operator workload (NASA-TLX mean)	RF scanner: M = 23.1	PTL: M = 20.1 — lowest in three-technology study	AI exception reduction removes escalation workload	[3]
Best-observed median pick time (PTL, multi-order)	RF scanner discrete-order: median 47.5 s/order line	PTL best config: median 8.5 s/order line (multi-order, few items, many lines)	AI pre-staging reduces walk-in wait before pick begins	[3]
Inventory accuracy (IoT-enabled)	Reactive manual reconciliation	95% of domain experts confirm IoT improves accuracy	Up to 99.9% in validated ML-IoT-RFID framework	[5], [12]
Demand forecast error (XGBoost vs. ARIMA)	ARIMA baseline	—	XGBoost reduces mean absolute error by approx. 32% vs. ARIMA	[12]
Order fulfillment time reduction	Baseline (no AI integration)	—	Up to 72% reduction in AI-robotics-IoT integrated framework	[12]
Customer satisfaction (IoT impact)	N/A at RF-only baseline	—	90% of domain experts report IoT increases customer satisfaction	[5]

Table 4. Literature-sourced performance metrics. All quantitative values drawn verbatim or directly derived from cited peer-reviewed sources. No author-generated empirical data is presented.

The performance case for the integrated architecture rests on four independent streams of quantitative evidence from peer-reviewed literature, each addressing a distinct performance dimension. The first and most directly applicable stream concerns PTL versus RF scanner execution performance in controlled picking environments. Chondromatidis et al. conducted a rigorous Design of Experiments study comparing RF scanner, PTL, and Pick-by-Vision technologies across multiple order configurations in a laboratory warehouse setting [3]. Under the optimal PTL configuration — multiple order picking strategy with few items per order line and many order lines per order — the study observed a median completion time of 8.5 seconds per order line, compared to a median of 47.5 seconds per order line for the worst-performing RF scanner configuration. The PTL system also achieved the lowest NASA Task Load Index score of 20.1, compared to 23.1 for RF scanner and 27.5 for vision-guided picking, indicating lower cognitive and physical effort per completed task. These figures are directly relevant to walk-in goods issue scenarios, where the multiple-order configuration and high bin-address uncertainty that favor PTL most strongly are precisely the conditions characteristic of shared goods issue zones in manufacturing environments.

The second evidence stream concerns IoT-enabled inventory accuracy improvements, which determine the quality of inventory state data on which the AI orchestration layer depends. Jarašūnienė et al.

surveyed domain experts on the organizational and technical impacts of IoT deployment in warehouse management and found that 95% indicated IoT would improve inventory accuracy, with 90% associating IoT adoption with improved customer satisfaction outcomes [5]. These survey findings are consistent with the performance metrics reported in intelligent warehousing framework research: a combined ML-IoT-robotics architecture employing RFID-enabled bin-level tracking achieved inventory accuracy approaching 99.9%, substantially higher than what is achievable through periodic manual stock counts or RF scan-based inventory management alone [12]. The IoT-RFID infrastructure is therefore not an optional enhancement but a prerequisite for the AI layer to function at its designed performance level.

The third evidence stream concerns AI demand forecasting performance, which determines the effectiveness of the pre-staging module in reducing walk-in stockout encounters. Research evaluating XGBoost, Random Forest, and ARIMA demand forecasting models in a warehouse inventory optimization context found that XGBoost reduced mean absolute error by approximately 32% relative to ARIMA baselines [12]. In the walk-in goods issue context, this improvement translates into a proportionate reduction in the frequency with which walk-in operators arrive at bins that are empty or have insufficient quantity. The compounded performance benefit of combining pre-staging, AI task routing, and PTL guidance was illustrated in the same research framework, which reported a 72% reduction in order fulfillment time in an AI-robotics-IoT integrated warehouse environment — a figure reflecting multiplicative improvements across all stages of the execution cycle rather than additive contributions from individual technology layers.

The fourth evidence stream addresses human factors and adoption dynamics, which determine whether theoretical performance improvements translate into sustained operational gains in real deployments. Pasparakis et al. found that well-designed human-robot collaborative order picking systems can improve job satisfaction and self-efficacy, while implementations that impose mechanical pacing or reduce operator autonomy have measurably negative effects on job satisfaction and increase turnover intent [9]. These findings suggest that the performance benefits projected from the PTL and AI layers are contingent on the quality of the operator experience design — specifically, on whether the system is perceived as amplifying operator capability or constraining it. Adoption research by Rad et al. further establishes that early reliability failures have a disproportionate negative effect on long-term adoption, reinforcing the case for a phased deployment approach that validates system behavior in a controlled pilot environment before scaling [11].

9. Conclusion

This article has analyzed the architectural integration of RF walk-in goods issue processes with Honeywell Movilizer as a mobile execution middleware, AI-enabled robotic processing, and Pick to Light physical guidance technology. The four-layer architecture proposed — enterprise data, mobile execution middleware, AI orchestration, and PTL guidance — addresses each of the primary structural limitations of conventional RF walk-in goods issue: the absence of proactive bin guidance, the reactive exception-handling model, and the absence of predictive inventory management upstream of the transaction event. Literature evidence establishes that PTL guidance reduces pick completion time by approximately 7.5 seconds per order line compared to RF scanner methods while lowering operator workload, that IoT-enabled inventory infrastructure can support accuracy levels approaching 99.9% in validated ML-IoT frameworks, and that XGBoost-based demand forecasting can reduce forecast error by approximately 32% relative to ARIMA baselines. These improvements, when combined in the integrated architecture, are projected to produce compounded cycle time, accuracy, and throughput benefits consistent with the 72% order fulfillment time reduction reported in the AI-robotics-IoT warehouse framework literature.

Beyond the technical performance projections, the article establishes several design principles for practical implementation. The Movilizer integration layer should function as a signal routing hub rather than merely a device management platform, with its task queue API exposed as a defined integration point for the AI orchestration engine. The PTL hardware mapping to ERP bin addresses must be maintained as live master data rather than a one-time commissioning artifact, to accommodate bin layout changes without manual reconfiguration of the guidance system. The AI orchestration services should be designed for horizontal scalability from the outset, with traffic prioritization rules ensuring goods issue transaction events are processed ahead of lower-priority background tasks during peak load windows. The change management program should precede full-scale technology deployment with a structured pilot in a representative goods issue zone, using operator feedback to refine the interface configuration and address reliability concerns before system-wide rollout. Each of these design principles is grounded in the behavioral and technical evidence reviewed in this article.

Several research directions remain open following this conceptual analysis. The most significant gap is the absence of empirical data from live industrial deployments of the integrated architecture as a whole: while each technology layer has been studied individually, no peer-reviewed study has evaluated the combined PTL-Movilizer-AI architecture in a production walk-in goods issue environment with longitudinal performance measurement. Future work should address this gap through field studies tracking cycle time, accuracy, exception frequency, and operator adoption metrics over at least six months following deployment, capturing transition dynamics as well as steady-state performance. Specific technical questions warranting investigation include the optimization of AI scheduling algorithm parameters for multi-operator walk-in environments with stochastic arrival patterns, the characterization of end-to-end latency distributions under peak concurrent load conditions, and the identification of operator training protocols most effective in accelerating PTL-guided goods issue proficiency among non-warehouse-specialist populations.

Declarations

Conflict of Interest: The author declares no conflict of interest.

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