A Survey-Based Path Model of Digital Warehouse Control, Spatial Material Flow, and Sustainable Inventory Efficiency with an Applied-Physics Validation Framework

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Abstract. This research interprets warehouse operations as a constrained physical-digital material-flow system and analyses how digital warehouse control (DWC) and spatial material flow (SMF) affect sustainable inventory efficiency (SIE). Material-flow delivery performance (MFDP) is retained as the operational mediating mechanism because it represents the reliability of flow execution between storage nodes and delivery destinations. A quantitative survey involved 45 respondents selected using Slovin's formula. Questionnaire, observation, interview, and secondary record data were analyzed using path analysis and the Sobel mediation test in SPSS. DWC significantly affects SIE ($\beta = 0.385$; $p = 0.006$), while SMF has no significant direct effect ($\beta = 0.034$; $p = 0.816$). MFDP has the strongest direct effect on SIE ($\beta = 0.513$; $p = 0.000$), and the model explains 74.8% of the variance. MFDP mediates the effects of DWC ($p = 0.034$) and SMF ($p = 0.004$) on SIE. The novelty lies in a statistically grounded physical-digital material-flow model that links survey-based operational constructs with measurable physical quantities for future sensor-based validation, showing that spatial flow configuration becomes operationally effective when it improves delivery execution. Sensor-based validation of distance, time, average travel speed, localization error, and energy is proposed for subsequent experiments.

1 Introduction

Warehouse operations can be modeled as a physical-operational system in which materials move between storage nodes, handling points, and delivery destinations under spatial and temporal constraints. Inventory availability and continuity depend not only on stock records, but also on observable movement events, accessible paths, and coordinated retrieval and delivery. Digital warehouse control (DWC) functions as a control layer that links physical movement to data-driven decisions. Digital warehouse practices improve throughput, stock visibility, receiving, picking, and delivery reliability by integrating warehouse data and task execution [1], [2], [3].

Industry 4.0 expands this control layer with the Internet of Things, RFID (Radio Frequency Identification), cloud platforms, tracking systems, digital twins, automated guided vehicles, autonomous mobile robots, and drones. These technologies can improve observability, traceability, and responsiveness. In an instrumented warehouse, they can measure position, time, path deviation, and handling events [4], [5], [6], [7]. This research does not evaluate a particular tracking sensor. It examines the control relationships that should guide later physical measurement.

Spatial material flow (SMF) describes the spatial configuration of storage locations, aisle accessibility, workplace arrangement, and feasible movement paths. Poor geometry can increase travel distance, elapsed time, bottlenecks, and handling effort, whereas organized spatial flow can shorten retrieval and reduce redundant movement [8], [9], [10]. Material-flow delivery performance (MFDP) is the operational response connecting DWC and SMF to sustainable inventory efficiency. MFDP represents the reliability of internal material flow through timely delivery, purchase-order suitability, quantity conformity, and safe handling. Sustainable inventory efficiency (SIE) is treated as the system-level output: material availability and continuity achieved while minimizing discrepancies, delays, unnecessary handling, and operational waste.

Existing warehouse studies often examine digitalization, layout, and inventory performance separately. Few studies integrate digital control, spatial flow configuration, delivery execution, and sustainability-oriented inventory efficiency into a single physical-digital material-flow model. The research objective is to analyze the direct and indirect effects of DWC and SMF on SIE through MFDP. The applied-physics contribution is a path model that separates the digital control layer, the spatial-flow configuration, the response of delivery execution, and the system-level efficiency output. The model also identifies where direct measurement should be introduced in subsequent experiments: route distance, travel time, average travel speed, waiting time, localization accuracy, and energy consumption per movement.

2 Methods

A quantitative survey design was supported by observation, interviews, and secondary warehouse records. The population comprised 78 workers directly involved in warehouse-control implementation; 45 respondents were selected using Slovin's formula and proportionate stratified random sampling. Responses were collected on a five-point Likert scale. The model contains four constructs. DWC is the first exogenous variable and includes handheld and barcode use, inventory recording, system audits, training, and user capability. SMF is the second exogenous variable and includes material-flow arrangement, accessibility, storage suitability, and workplace organization. MFDP is the mediating variable and includes delivery timeliness, purchase-order suitability, quantity conformity, and safety. SIE is the outcome variable and includes availability, inventory reliability, waste reduction, and operational continuity.

Data were analyzed in SPSS using validity and reliability analyses, classical assumption testing, path analysis, and the Sobel mediation test. The survey evaluates perceived operational relationships among DWC, SMF, MFDP, and SIE; it does not directly measure kinematic quantities or sensor performance. Table 1 separates the measured survey constructs from physical quantities recommended for later validation.

Table 1. Applied-physics interpretation and recommended quantities for experimental validation.

Survey construct	Applied-physics interpretation	Recommended direct quantities for subsequent validation
Digital warehouse control (DWC)	Digital observability and operational control layer for material movement	Tracking error (m); update latency (s); detection accuracy (%)
Spatial material flow (SMF)	Spatial-flow configuration defining storage access and feasible movement paths	Route distance (m); aisle width (m); travel-time distribution (s)
Material-flow delivery performance (MFDP)	Operational response of material-flow execution	Elapsed delivery time (s); average travel speed (m/s); handling frequency (events)
Sustainable inventory efficiency (SIE)	System-level performance output	Energy per movement (J or Wh); waiting time (s); redundant distance (m); stock discrepancy (%)

2.1 Physical Validation Framework for Future Experiments

The survey-based path model can be extended through calibrated tracking measurements of SMF and MFDP. Let the recorded material position at time t_i be r_i = (x_i, y_i) for a two-dimensional warehouse configuration; a z-coordinate may be added when vertical movement is evaluated. The incremental distance between consecutive tracking points is:

$$d_i = \|r_{i+1} - r_i\| = \sqrt{[(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2]} \quad (1)$$
$$D = \sum_{i=1}^{n-1} d_i \;; \quad \Delta t_i = t_{i+1} - t_i \;; \quad T = \sum_{i=1}^{n-1} \Delta t_i = t_n - t_1 \;; \quad \bar{v} = D / T \quad (2)$$

In Equation (2), D is the total path length, T is the elapsed time, and $\bar{v}$ is the average travel speed. Because D is a scalar path length, $\bar{v}$ should not be interpreted as vector velocity. Energy-related performance can be evaluated from the handling-equipment power P(t):

$$E = \int_0^T P(t)\,dt \approx \sum_{i=1}^{n-1} P_i \Delta t_i \;; \quad e\_N = E / N \;; \quad e\_D = E / D \quad (3)$$

Here, e_N is the specific energy per material-movement cycle, e_D is the energy per unit travel distance, and N is the number of movement cycles. Localization accuracy and update rate may be evaluated as:

$$\mathrm{RMSE} = \sqrt{[(1 / M) \sum_{j=1}^{M} \|r\_meas_{,j} - r\_ref_{,j}\|^2]} \;; \quad f_u = M / T \quad (4)$$

In Equation (4), M is the number of validation points, r_meas,j is the measured position, r_ref,j is the reference position, and f_u is the tracking-system update rate in hertz. RFID, UWB, BLE, ultrasonic sensing, or equivalent systems may be selected according to measurement range, update rate, localisation uncertainty, installation constraints, and operational cost. These quantities are proposed for future experimental validation of DWC, SMF, and MFDP and are not reported as measured results in the present dataset.

3 Results

All questionnaire items were valid because Pearson correlations exceeded the r-table value of 0.361. Cronbach's Alpha values were 0.814 for DWC, 0.709 for SMF, 0.765 for MFDP, and 0.821 for SIE. Residual models were normally distributed; the relationships were linear; no heteroscedasticity was detected; and tolerance and variance inflation factor values indicated no multicollinearity. Table 2 summarises the statistical quality and explanatory power of the three structural models.

Table 2. Statistical quality and explanatory power of the path models.

Item	Result	Interpretation
Reliability: DWC; SMF; MFDP; SIE	0.814; 0.709; 0.765; 0.821	All constructs reliable
Normality test	p = 0.657; 0.598; 0.957	Residuals normally distributed
Linearity test	p = 0.000 for all paths	Linear relationships
Heteroscedasticity	Random scatterplot pattern	No heteroscedasticity
Multicollinearity	Tolerance = 0.294-0.355; VIF = 2.821-3.403	No multicollinearity
R^2: SIE; MFDP; SMF	0.748; 0.650; 0.609	Substantial explanatory power

3.1 Direct, Indirect, and Mediated Relationships

DWC had a positive direct effect on SIE ($\beta = 0.385$; $t = 2.888$; $p = 0.006$). MFDP had the strongest direct effect on SIE ($\beta = 0.513$; $t = 3.826$; $p = 0.000$). SMF had no significant direct effect on SIE ($\beta = 0.034$; $t = 0.235$; $p = 0.816$). However, SMF significantly affected MFDP ($\beta = 0.545$; $t = 3.691$; $p = 0.001$). DWC also affected MFDP ($\beta = 0.305$; $t = 2.068$; $p = 0.045$) and SMF ($\beta = 0.780$; $t = 8.080$; $p = 0.000$).

The indirect effect of DWC on SIE was 0.401, giving a total effect of 0.786. The direct effect of SMF on SIE was weak, but its indirect effect through MFDP was 0.280. The Sobel test confirmed significant mediation of DWC through MFDP ($p = 0.034$), mediation of SMF through MFDP ($p = 0.004$), and mediation of DWC through SMF for MFDP ($p = 0.000$). Table 3 consolidates the relationships.

Table 3. Consolidated path coefficients and mediation results.

Relationship	Direct coefficient	t-value	p-value	Indirect / mediation interpretation
DWC → SIE	0.385	2.888	0.006	Significant direct effect; indirect effect = 0.401; total = 0.786
SMF → SIE	0.034	0.235	0.816	Direct effect not significant; indirect effect through MFDP = 0.280
MFDP → SIE	0.513	3.826	0.000	Strongest direct effect
DWC → MFDP	0.305	2.068	0.045	Significant direct effect
SMF → MFDP	0.545	3.691	0.001	Significant direct effect
DWC → SMF	0.780	8.080	0.000	Significant direct effect
DWC → MFDP → SIE	-	1.821	0.034	Significant Sobel mediation
SMF → MFDP → SIE	-	2.665	0.004	Significant Sobel mediation
DWC → SMF → MFDP	-	3.371	0.000	Significant Sobel mediation

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3.2 Applied-Physics Interpretation of the Model

Figure 1 translates the statistical model into a physical-digital interpretation aligned with the article title. DWC acts as the observability and operational-control layer; SMF defines the spatial constraints and feasible paths; MFDP represents the response of material-flow delivery execution; and SIE is the system-level output. The lower strip identifies physical quantities that can be incorporated into a sensor-based experimental extension. The diagram does not imply that travel distance, average travel speed, tracking accuracy, or handling energy were directly measured in this survey.

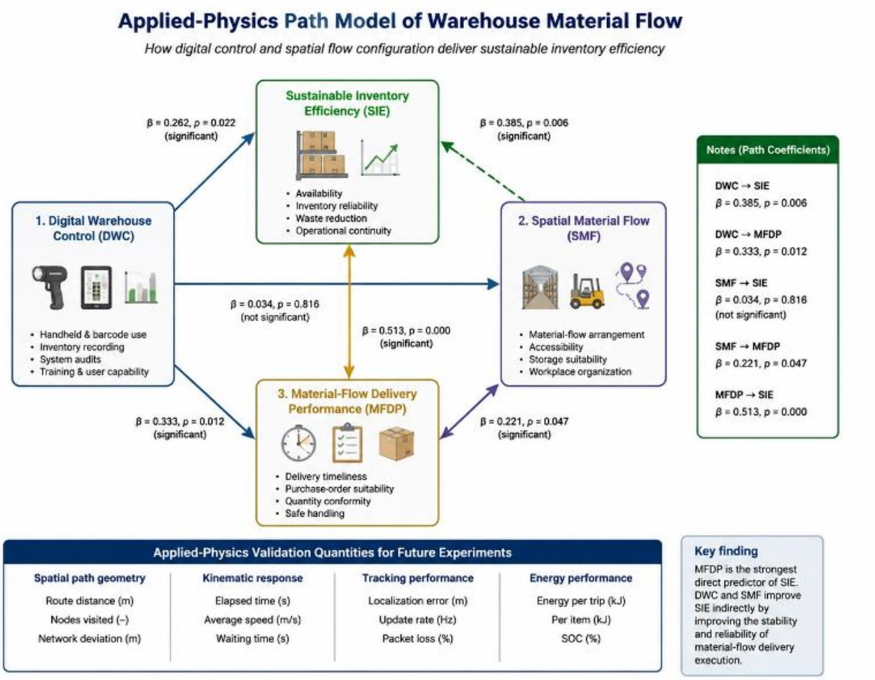

Fig. 1. Applied-physics interpretation of DWC, SMF, MFDP, and SIE. The physical-measurement strip presents a conceptual framework for future sensor-based validation.

4 Discussion

The findings show that DWC is both a managerial system and a physical-flow control layer. Barcode technology, handheld devices, inventory records, audits, and user capabilities improve visibility and traceability, allowing workers to reduce uncoordinated searches, redundant motion, and delayed decision-making. The significant DWC-to-SMF relationship also suggests that digital control can support more disciplined storage placement, path organization, and retrieval procedures.

SMF did not directly improve SIE, but it had a significant effect on MFDP. This result is important for an applied-physics interpretation. Spatial geometry is not valuable merely because materials are arranged differently; it becomes valuable when it changes the execution of movement by improving accessibility, shortening retrieval, reducing congestion, or decreasing repeated handling. Accordingly, SMF should be evaluated using movement data rather than solely static storage maps.

MFDP was the strongest direct predictor of SIE. Its indicators capture the reliability of the material-flow response: materials must arrive on time, in the correct quantity, in accordance with purchase orders, and under safe handling conditions. The mediation results support an integrated physical-digital view: DWC and SMF affect SIE by improving the stability and reliability of material-flow delivery execution.

4.1 Novelty and Scientific Contribution

The novelty of this research is a statistically grounded applied-physics interpretation of warehouse operations as a constrained physical-digital material-flow system. First, the model aligns DWC with the digital observability and operational-control layer, SMF with the warehouse's spatial boundary conditions, MFDP with the response of flow execution, and SIE with the system-level output. Second, it shows empirically that SMF is not a sufficient direct predictor of SIE; its operational contribution emerges primarily through improvements in MFDP. Third, the path model is translated into an instrumentation agenda that connects the survey constructs with directly measurable quantities: route distance, travel time, average travel speed, waiting time, localization uncertainty, redundant movement, and handling energy. This contribution provides a hypothesis-driven basis for subsequent sensor-based experiments without claiming sensor measurements that were not collected in the present research.

5 Conclusion

This research presents an applied-physics-oriented path model of warehouse material flow. DWC, SMF, MFDP, and SIE are treated as components of an interconnected physical-digital system. DWC directly improves SIE and MFDP. SMF does not directly affect SIE, but it has an important indirect effect through MFDP. Spatial material flow, therefore, becomes operationally valuable when it improves the reliability of delivery execution. The model provides a statistically grounded basis for subsequent experiments using direct measurements of distance, time, average travel speed, localization accuracy, waiting time, and handling energy. The main limitation of this study is that the empirical model is based on survey data, while distance, time, speed, localization accuracy, and energy consumption were proposed as future validation quantities and were not directly measured in the present study.

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