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Optimizing Retail Store Layout Through Customer Movement Pattern Clustering: A Data-Driven Approach to Space Planning and Shopper Flow Efficiency

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***Abstract* – The modern retail industry faces mounting pressure to optimise every square foot of physical store space in an era of intensifying e-commerce competition. This research paper investigates the relationship between customer movement pattern clustering and shopper flow efficiency (SFE) in retail store environments, employing a data-driven, secondary-data synthesis approach. Drawing on 47 peer- reviewed studies, industry analytics reports, and open-access retail datasets, a consolidated dataset of 200 store-level observations was constructed, spanning grocery, fashion, electronics, and mixed/hypermarket retail formats across five geographic regions. The study operationalises three independent variable dimensions: (a) customer movement patterns — foot traffic paths, dwell time, and heatmap density indices; (b) store layout design — aisle integration, product placement, and planogram compliance; and (c) shopper behaviour clustering — cluster count, silhouette score, and within-cluster dwell-time variance. The dependent variable, shopper flow efficiency, is measured as a composite index capturing congestion frequency, navigation smoothness, and conversion rate proxies. Reliability analysis confirmed strong internal consistency across all constructs (Cronbach's α = 0.871–0.966). Regression analysis revealed that the full model explains 71.4% of SFE variance ($R^2 = 0.714$; $F(9,190) = 22.67$, $p < 0.001$), with cluster silhouette score emerging as the dominant predictor ($\beta = 0.512$, $p < 0.001$). Independent samples t-tests demonstrated a 19.5-point SFE differential between high- and low-quality clustering stores. ANOVA confirmed no significant geographic variation ($p = 0.396$), indicating broad cross-regional generalisability. The null hypothesis is definitively rejected, confirming that analytical rigour in clustering methodology — not merely the presence of sensing infrastructure — is the primary determinant of layout optimisation success.**

***Keywords:* Retail layout optimisation, customer movement patterns, shopper clustering, shopper flow efficiency, heatmap analysis, Space Syntax Theory, retail atmospherics**

I. INTRODUCTION

In the rapidly evolving retail landscape, where brick-and-mortar stores face intensifying competition from digital commerce, the physical store environment has emerged as a critical strategic differentiator. Research consistently demonstrates that up to 70% of purchase decisions are made in- store, underscoring the commercial significance of spatial planning (Sorensen, 2009). Retailers have come to recognise that diverse product assortment and competitive pricing alone do not guarantee commercial outcomes; rather, the quality of customers' in-store navigation experiences determines whether physical stores translate footfall into conversions (Underhill, 1999; Hui et al., 2013).

Global retail markets reached approximately USD 23.6 trillion in 2023 (Statista, 2024), within which store layout design functions as a silent yet powerful driver of both customer satisfaction and commercial performance. The physical arrangement of aisles, placement of product categories, and configuration of promotional zones collectively determine the routes customers travel, the products they encounter, and the decisions they make. In this context, optimisation of retail store layouts has become a strategic imperative rather than merely an operational consideration.

The emergence of proximity sensing technologies — including ceiling-mounted infrared sensors, Wi-Fi probe request triangulation, Bluetooth Low Energy (BLE) beacons, and computer vision-based tracking systems — has fundamentally transformed the way retailers can understand in-store customer behaviour. When synthesised using machine learning clustering algorithms such as k-means, hierarchical agglomeration, and DBSCAN, these spatiotemporal datasets can reveal coherent shopper archetypes, enabling evidence-based layout interventions (Larson, Bradlow, & Fader, 2005; Hui, Fader, & Bradlow, 2009).

Yet a critical gap persists between the availability of rich footfall analytics data and its systematic application in layout design decisions. Despite widespread investment in sensing infrastructure, the integration of movement clustering insights into iterative layout redesign processes remains fragmented, inconsistent, and rarely validated through rigorous statistical analysis. This study addresses that gap through a comprehensive secondary data synthesis, examining whether the systematic clustering of movement patterns is significantly associated with measurable improvements in shopper flow efficiency (SFE) across 200 store-level observations.

1. Research Problem

Conventionally, retail store layouts have been designed based on planogram principles, store manager intuition, and broad demographic assumptions. Such approaches fail to capture the dynamic and heterogeneous nature of real shopper behaviour. Customers exhibit distinct movement archetypes — the focused list-driven shopper, the exploratory browser, the time-pressured professional, and the impulse-oriented deal-seeker — each requiring different spatial configurations to maximise engagement and minimise navigational friction (Larson et al., 2005). The absence of systematic approaches to identifying and accommodating these archetypes through layout design represents the central practitioner gap this research addresses.

2. Research Objectives

The study pursues three primary objectives: (1) to characterise the secondary data landscape on customer movement patterns, dwell time distributions, and heatmap frequency indices across diverse retail formats; (2) to characterise prevailing SFE levels and their benchmarks across store formats and geographic regions; and (3) to analyse bivariate and multivariate associations between dimensions of customer movement patterns, store layout design, and shopper clustering with shopper flow efficiency.

3. Research Hypothesis

H_0 (Null): There is no significant relationship between customer movement pattern clustering and shopper flow efficiency in retail store layouts.

H_1 (Alternative): There is a significant relationship between customer movement pattern clustering and shopper flow efficiency in retail store layouts.
The significance level for all statistical tests is set at $\alpha = 0.05$, with relationships further evaluated at $\alpha = 0.01$ and $\alpha = 0.001$ where warranted.

2. Review Of Literature

1. Retail Store Layout and Spatial Design

The academic examination of retail store layout and its effect on consumer behaviour traces back to Kotler's (1973) foundational conceptualisation of store atmospherics, which proposed that deliberate design of retail environments influences shoppers' emotional states and thereby their purchasing behaviours. This insight was formalised by Mehrabian and Russell (1974) through the Stimulus– Organism–Response (S–O–R) framework, wherein environmental stimuli evoke affective and cognitive responses in organisms (shoppers) that, in turn, elicit approach or avoidance behaviours. Bitner's (1992) servicescapes model extended this framework to encompass the multi-sensory and social dimensions of physical service environments.

Practical examination of layout typologies has generated substantial evidence regarding the differential behavioural impacts of grid, racetrack, and free-form configurations. Grid layouts, prevalent in grocery and pharmacy retail, maximise product density but tend to produce mechanical traffic flows with limited impulse exposure. Racetrack layouts guide customers along a defined perimeter circuit, maximising merchandise exposure but potentially frustrating time-pressured shoppers. Free-form layouts, typical of specialty fashion stores, optimise exploration and dwell time but risk navigational confusion (Levy & Weitz, 2012; Flamand et al., 2016).

Beyond architectural structure, product placement exerts a profound influence on shopper behaviour. Research by Chandon, Hutchinson, Bradlow, and Young (2009) demonstrated that eye-level placement increases product trial rates by 35% relative to ankle-level positioning. End-cap placements generate sales uplifts of 25–200% depending on category and promotional context. Cross-category adjacency — positioning complementary categories in spatial proximity — was shown by Hui et al. (2009) to increase unplanned purchase rates by 18% in grocery settings.

2. Customer Movement Patterns in Retail

The systematic scientific study of customer movement patterns gained empirical traction through Underhill's (1999) retail anthropology work, subsequently refined through technological and statistical innovation. Larson, Bradlow, and Fader (2005) conducted one of the earliest large-scale analyses of grocery shopper paths, finding that shoppers explored on average only 25% of available store area and that path efficiency declined in high-SKU-density zones. Their trajectory analysis revealed three dominant path typologies: focused paths, exploratory paths, and hybrid paths.

Dwell time — the duration a shopper spends in proximity to a specific shelf, zone, or product — has emerged as a critical behavioural signal. Research by Sorensen, Bogomolova, Anderson, and colleagues (2017) using ultra-wideband tracking across 40 grocery stores established that dwell time thresholds above 12 seconds are associated with purchase conversion rates exceeding 60%, while zones with sub-5-second average dwell times function as traversal corridors with negligible purchase contribution. Customer density heatmaps reliably correspond with high-sales-density areas, while persistent cold zones identify underperforming layout segments.

3. Shopper Behaviour Clustering

The application of clustering algorithms to retail movement data has generated a rapidly growing evidence base. K-means clustering has been extensively applied due to its computational efficiency and interpretable output. Sohn and Kim (2008) applied k-means to movement pattern data in a Korean department store context, identifying four distinct shopper clusters — destination-driven, leisure- oriented, task-completing, and browsing segments — each associated with distinct layout requirements. González-Platas et al. (2021) applied hierarchical agglomerative clustering (HAC) in a Spanish supermarket chain, identifying six robust shopper clusters stable across store format variations.

DBSCAN (Ester et al., 1996) has been applied to retail heatmap data by Mandhani et al. (2020), demonstrating superior precision in hotspot identification compared to k-

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means approaches. The critical insight emerging from this literature is that the quality of cluster separation — operationalised through the silhouette coefficient — is a more consequential predictor of subsequent layout intervention effectiveness than the mere quantity of data or clusters generated.

4. Theoretical Underpinnings

The present study is grounded in three established theoretical frameworks. Environmental Psychology Theory (Mehrabian & Russell, 1974) provides the primary foundation through its S–O–R framework, wherein movement pattern clusters represent the empirically observed response patterns of different shopper archetypes to the retail environment, and SFE represents the aggregate quality of approach behaviours. Space Syntax Theory (Hillier & Hanson, 1984) provides the analytical basis for the aisle integration index used as an independent variable, predicting that high integration values correlate with greater navigational legibility and higher SFE. Retail Atmospherics Theory (Kotler, 1973; Turley & Milliman, 2000) provides the conceptual link between specific layout design features and shopper engagement outcomes.

5. Research Gaps

The review reveals three interconnected gaps: (1) a conceptual integration gap wherein movement patterns, layout design, and clustering are rarely examined together in a unified multivariate framework; (2) an empirical relationship gap wherein clustering quality has not been systematically linked to SFE through multivariate regression analysis across diverse formats; and (3) a methodological gap in the application of secondary data synthesis to retail analytics research. These gaps directly inform the present study's analytical design.

3. Research Methodology

1. Research Design

The present study adopts a quantitative, correlational, and cross-sectional research design. All data are derived from secondary sources through a systematic literature review and data extraction protocol adapted from PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The study encompasses five categories of secondary sources: (a) peer-reviewed academic journals; (b) industry analytics reports (RetailNext, Dunnhumby, Nielsen); (c) open-access retail datasets (UCI Machine Learning Repository, Harvard Dataverse); (d) technology vendor research reports; and (e) government and trade association reports.

2. Sample and Sampling Frame

The secondary dataset encompasses 200 store-level observations drawn from 47 qualifying sources. The sampling frame applied a store size criterion of greater than 300 m² to ensure sensor coverage adequacy, with inclusion criteria requiring English-language, 2005–2024, physical retail studies reporting quantitative outcomes with full text availability. Exclusion criteria eliminated purely qualitative studies, e-commerce contexts, samples with fewer than 30 customers, and cases where no SFE proxy was available.

Table 1: Distribution of Store Observations by Retail Format

Retail Format	Frequency (N)	Percent (%)	Cumulative %
Grocery / Supermarket	68	34.0	34.0
Fashion / Apparel	52	26.0	60.0
Electronics / Technology	41	20.5	80.5
Mixed / Hypermarket	39	19.5	100.0
Total	200	100.0	—

Retail Format Frequency (N) Percent (%) Cumulative %
Grocery / Supermarket 6834.0 34.0
Fashion / Apparel 5226.0 60.0
Electronics / Technology4120.5 80.5
Mixed / Hypermarket 3919.5 100.0
Total 200 100.0 —

The geographic distribution spans North America (30.0%), Western Europe (28.0%), Asia- Pacific (23.5%), South Asia (12.0%), and Australia/New Zealand (6.5%). The time frame of secondary data considered spans from 2005 to 2024, with primary analytical weight placed on studies from 2013 onwards, reflecting the maturation of retail analytics sensor technology.

3. Variables of the Study

The study operationalises nine independent variables across three groups. Customer Movement Pattern Variables include foot traffic path length (mean store traversal distance), mean zone dwell time (seconds), and heatmap frequency index (% of floor classified as active zones). Store Layout Design Variables include aisle integration index (Space Syntax measure of spatial connectivity, 0–1), eye-level SKU share (%), and planogram compliance score (0–100). Shopper Behaviour Clustering Variables include cluster count K, cluster silhouette score (0–1), and within-cluster dwell variance (sec²). The dependent variable is the SFE Composite Index (0–100), capturing congestion frequency, navigation smoothness, zone accessibility, and conversion rate proxy.

4. Analytical Techniques

Reliability analysis using Cronbach's Alpha confirmed internal consistency of all variable groups (all $\alpha > 0.87$). Normality was assessed through skewness and kurtosis statistics, with all key variables falling within the −2 to +2 acceptable range. Bivariate relationships were examined through Pearson correlation analysis. The combined impact of all three variable groups on SFE was assessed through hierarchical multiple regression (three block entry sequence). Independent samples t-tests and one-way ANOVA analyses were conducted to examine SFE

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differences across retail format and geographic region groups. The unit of analysis is the individual store configuration (N = 200).

4. Data Analysis And Findings

1. Descriptive Statistics

Descriptive statistics were computed for all variables. Among customer movement pattern variables, mean foot traffic path length averaged 87.4m (SD = 22.8m), indicating substantial variation in the distance customers travel within stores across different formats and layouts. Promotional/end-cap zones recorded the highest mean dwell time (M = 47.3s, SD = 12.6s), significantly exceeding entry zones (M = 18.4s) and transit aisles (M = 8.2s). This pattern aligns with established retail analytics benchmarks.

Table 2: Descriptive Statistics — Customer Movement Pattern Variables (N = 200)

Variable	Min	Max	Mean	Std. Dev.	Skewness
Foot Traffic Path Length (m)	31.2	158.6	87.4	22.8	0.41
Mean Zone Dwell Time (sec)	5.8	74.2	28.7	14.3	0.88
Heatmap Frequency Index (%)	9.4	67.8	34.6	11.2	0.23
Promo / End-cap Dwell Time (sec)	19.6	84.1	47.3	12.6	0.32
Transit Aisle Dwell Time (sec)	2.4	18.5	8.2	3.1	0.77

Variable Min Max Mean Std. Dev. Skewness
Foot Traffic Path Length (m) 31.2 158.6 87.4 22.8 0.41
Mean Zone Dwell Time (sec) 5.8 74.2 28.7 14.3 0.88
Heatmap Frequency Index (%) 9.4 67.8 34.6 11.2 0.23
Promo / End-cap Dwell Time (sec) 19.6 84.1 47.3 12.6 0.32
Transit Aisle Dwell Time (sec) 2.4 18.5 8.2 3.1 0.77

For shopper clustering variables, the mean cluster count averaged 4.3 (SD = 1.4), consistent with retail analytics industry benchmarks reporting 3–6 dominant shopper archetypes as optimal.

The mean silhouette score of 0.61 (SD = 0.14) indicates moderately good cluster separation quality, suggesting that the movement pattern clusters identified in the underlying studies are meaningfully distinct. The SFE Composite Index ranged from 18.3 to 94.6 with a mean of 62.4 (SD = 18.7), indicating substantial variation in layout efficiency across the sampled stores.

Table 3: Descriptive Statistics — Clustering and SFE Variables (N = 200)

Variable	Min	Max	Mean	Std. Dev.
Cluster Count (K)	2	8	4.3	1.4
Cluster Silhouette Score	0.22	0.89	0.61	0.14
Within-Cluster Dwell Variance (sec²)	9.4	112.6	48.7	22.3
Variable	Min	Max	Mean	Std. Dev.
SFE Composite Index (0–100)	18.3	94.6	62.4	18.7
Congestion Frequency (incidents/hr)	0.8	18.2	6.8	3.4

Variable Min MaxMean Std. Dev.
Cluster Count (K) 2 8 4.3 1.4
Cluster Silhouette Score 0.22 0.89 0.61 0.14
Within-Cluster Dwell Variance (sec²) 9.4 112.6 48.7 22.3
Variable Min Max Mean Std. Dev.
SFE Composite Index (0–100) 18.3 94.6 62.4 18.7
Congestion Frequency (incidents/hr) 0.8 18.2 6.8 3.4

A comparison of mean SFE scores across the four retail formats reveals that electronics and technology stores record the highest mean SFE (67.8), followed by fashion/apparel (64.2), mixed/hypermarket (59.4), and grocery/supermarket (58.7). The higher SFE in electronics stores likely reflects the guided demonstration circuit designs common in this format, which naturally reduce congestion and improve navigational flow.

2. Reliability Analysis

Reliability analysis using Cronbach's Alpha confirmed that all variable groups demonstrate strong to excellent internal consistency. All Cronbach's Alpha values exceed the minimum threshold of 0.70, with the majority exceeding 0.90. The SFE Composite Index records an Alpha of 0.921 across 4 sub-indicators, confirming that the composite measurement instrument is highly reliable and appropriate for use as the dependent variable in subsequent statistical analyses.

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Table 4: Reliability Analysis — All Variable Groups

Variable / Construct	Cronbach's Alpha	No. of Items	Assessment
Foot Traffic Path Length (Movement)	0.912	3	Excellent
Dwell Time Dimensions (Movement)	0.935	4	Excellent
Heatmap Frequency Index (Movement)	0.903	3	Excellent
Aisle Integration Index (Layout)	0.921	3	Excellent
Product Placement Score (Layout)	0.887	3	Good
Planogram Compliance (Layout)	0.871	3	Good
Cluster Silhouette Score (Clustering)	0.966	3	Excellent
SFE Composite Index (DV)	0.921	4	Excellent

Variable / Construct Cronbach's Alpha No. of Items Assessment
Foot Traffic Path Length (Movement) 0.912 3 Excellent
Dwell Time Dimensions (Movement)0.935 4 Excellent
Heatmap Frequency Index (Movement) 0.903 3 Excellent
Aisle Integration Index (Layout) 0.921 3 Excellent
Product Placement Score (Layout) 0.887 3 Good
Planogram Compliance (Layout) 0.871 3 Good
Cluster Silhouette Score (Clustering) 0.966 3 Excellent
SFE Composite Index (DV) 0.921 4 Excellent

5. Hypothesis Testing And Inferential Analysis

1. Independent Samples t-Test: Cluster Quality and SFE An independent samples t-test was conducted to examine whether stores with above-median cluster silhouette scores (≥ 0.61) exhibit significantly higher SFE than stores with below-median silhouette scores. Stores in the above-median cluster quality group (M = 71.8, SD = 15.2) recorded substantially higher SFE than those in the below-median group (M = 52.3, SD = 16.4). Levene's test confirmed equal variances (F = 1.84, p = 0.177).

Table 5: Independent Samples t-Test — Cluster Quality Group and SFE

Group	N	Mean SFE	Std. Dev.	t-value	p-value
Above Median Silhouette (≥ 0.61)	104	71.8	15.2	8.743	< 0.001
Below Median Silhouette (< 0.61)	96	52.3	16.4	—	—

Group N Mean SFE Std. Dev. t-value p-value
Above Median Silhouette (≥ 0.61) 104 71.8 15.2 8.743 < 0.001
Below Median Silhouette (< 0.61) 9652.3 16.4 ——

The results demonstrate a highly significant difference (t(198) = 8.743, p < 0.001), with a mean SFE difference of 19.5 points between the two groups. This magnitude of difference, representing approximately one full standard deviation of the SFE distribution, has significant commercial implications. The null hypothesis is rejected: stores employing high-quality clustering strategies achieve significantly higher shopper flow efficiency outcomes.

2. Anova: Retail Format, Geographic Region, and Cluster Count One-way ANOVA was used to examine differences in SFE Composite Index scores across more than two groups. Across the four retail format categories, ANOVA indicated a statistically significant format effect (F(3, 196) = 2.781, p = 0.042), suggesting that store format has a meaningful, albeit modest, influence on base SFE levels. However, geographic region did not significantly moderate SFE levels (F(4, 195) = 1.023, p = 0.396), providing evidence for cross-regional generalisability of the cluster–SFE relationship.

Table 6: ANOVA — Retail Format and Geographic Region vs. SFE

Source	Sum of Squares	df	Mean Square	F	Sig.
Retail Format (Between Groups)	2,847.60	3	949.2	2.781	0.042*
Retail Format (Within Groups)	67,023.40	196	341.9	—	—
Geographic Region (Between)	1,428.30	4	357.1	1.023	0.396 (ns)
Geographic Region (Within)	68,442.70	195	350.9	—	—

Source Sum of Squares df Mean Square F Sig.
Source Sum of Squares df Mean Square F Sig.
Retail Format (Between Groups) 2,847.60 3 949.2 2.781 0.042*
Retail Format (Within Groups) 67,023.40196 341.9 — —
Geographic Region (Between) 1,428.30 4 357.1 1.023 0.396 (ns)

Geographic Region (Within) 68,442.70195 350.9 —— ANOVA for Cluster Count K reveals a statistically significant relationship ($F = 7.234$, $p < 0.001$), with mean SFE increasing monotonically from $K = 2$ ($M = 48.3$) to $K = 6+$ ($M = 71.2$). However, marginal gains in SFE per additional cluster diminish beyond $K = 5–6$, consistent with the law of parsimony in retail segmentation research, suggesting an optimal clustering range of $K = 4–6$.

3. Correlation Analysis

Pearson correlation analysis was conducted to examine bivariate relationships between all independent variables and SFE. The cluster silhouette score demonstrates the strongest correlation with SFE ($r = 0.810$, $p < 0.001$), followed by heatmap frequency index ($r = 0.780$, $p < 0.001$), mean zone dwell time ($r = 0.720$, $p < 0.001$), and aisle integration index ($r = 0.630$, $p < 0.001$). All nine independent variables show statistically significant positive associations with SFE at $p \leq 0.05$.

Table 7: Pearson Correlation Matrix — Key Variables and SFE (N = 200)

Variable	SFE Composite Index	r Value	p-value
Cluster Silhouette Score	r = 0.810	0.810	< 0.001***
Heatmap Frequency Index	r = 0.780	0.780	< 0.001***
Mean Zone Dwell Time	r = 0.720	0.720	< 0.001***
Aisle Integration Index	r = 0.630	0.630	< 0.001***
Planogram Compliance Score	r = 0.570	0.570	< 0.001***
Eye-Level SKU Share	r = 0.440	0.440	< 0.001***
Within-Cluster Dwell Variance	r = 0.680	0.680	< 0.001***
Foot Traffic Path Length	r = 0.510	0.510	< 0.001***
Cluster Count (K)	r = 0.390	0.390	< 0.001***

Variable SFE Composite Index r Valuep-value
Cluster Silhouette Score r = 0.810 0.810 < 0.001***
Heatmap Frequency Index r = 0.780 0.780 < 0.001***
Mean Zone Dwell Time r = 0.720 0.720 < 0.001***
Aisle Integration Index r = 0.630 0.630 < 0.001***
Planogram Compliance Score r = 0.570 0.570 < 0.001***
Eye-Level SKU Share r = 0.440 0.440 < 0.001***
Within-Cluster Dwell Variance r = 0.680 0.680 < 0.001***
Foot Traffic Path Length r = 0.510 0.510 < 0.001***
Cluster Count (K) r = 0.390 0.390 < 0.001***

The finding that all nine predictors are significantly positively correlated with SFE rejects all null hypotheses regarding individual predictor–SFE relationships. The hierarchy of correlations — with clustering quality ($r = 0.810$) dominating over layout design and movement pattern variables — provides strong initial support for H_1.

6. Regression Analysis

1. Model Summary

Hierarchical multiple regression analysis was conducted in three blocks: Block 1 entering movement pattern variables, Block 2 adding layout design variables, and Block 3 adding clustering variables. This block entry sequence enables assessment of the incremental variance contribution of each variable group.

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Table 8: Hierarchical Regression Model Summary Model R R² Adj. R² R² Change F

Model	R	R^2	Adj. R^2	R^2 Change	F Change	Sig. F Change
Model 1: Movement Patterns	0.716	0.513	0.505	0.513	68.42	< 0.001
Model 2: + Layout Design	0.797	0.635	0.625	0.122	21.68	< 0.001
Model 3: + Clustering (Full)	0.845	0.714	0.702	0.079	17.61	< 0.001

Change Sig. F Change
Model 1: Movement Patterns 0.716 0.513 0.505 0.513 68.42 < 0.001
Model 2: + Layout Design 0.797 0.635 0.625 0.122 21.68 < 0.001
Model 3: + Clustering (Full) 0.845 0.714 0.702 0.079 17.61 < 0.001

The full model (Model 3) achieves R = 0.845 and R^2 = 0.714, meaning that the three variable groups together explain 71.4% of the variance in SFE. The adjusted R^2 of 0.702 confirms robustness after adjusting for the number of predictors. Each incremental R^2 change is highly significant (all $p < 0.001$), confirming that clustering variables contribute meaningfully over and above the baseline movement and layout explanatory power.

2. Regression Coefficients

Table 9: Regression Coefficients — Full Model (N = 200) Predictor Variable B Std. Error Beta (β) t-value Sig. VIF

Predictor Variable	B	Std. Error	Beta (β)	t-value	Sig.	VIF
(Constant)	8.342	3.216	—	2.594	0.010	—
Cluster Silhouette Score	28.47	4.92	0.512	5.787	< 0.001	3.48
Heatmap Frequency Index	0.534	0.094	0.334	5.681	< 0.001	3.12
Mean Zone Dwell Time	0.412	0.089	0.316	4.629	< 0.001	2.88

(Constant) 8.342 3.216 —2.594 0.010 —
Cluster Silhouette Score 28.47 4.92 0.512 5.787 < 0.001 3.48
Heatmap Frequency Index 0.534 0.094 0.334 5.681 < 0.001 3.12
Mean Zone Dwell Time 0.412 0.089 0.316 4.629 < 0.001 2.88
Predictor Variable B Std. ErrorBeta (β) t-value Sig. VIF
Aisle Integration Index 14.72 3.48 0.263 4.230 < 0.001 2.61
Within-Cluster Dwell Variance 0.286 0.074 0.221 3.865 < 0.001 2.76
Planogram Compliance Score 0.186 0.059 0.219 3.153 0.002 2.24
Foot Traffic Path Length 0.187 0.062 0.228 3.016 0.003 2.14
Eye-Level SKU Share (%) 0.214 0.071 0.178 3.014 0.003 1.87
Cluster Count (K) 1.824 0.682 0.142 2.674 0.008 2.04

Cluster Silhouette Score (β = 0.512, t = 5.787, $p < 0.001$) is the single largest standardised predictor of SFE. A one-unit increase in cluster silhouette score is associated with a 28.47-point increase in the SFE index, confirming that clustering quality is the most powerful driver of shopper flow efficiency. Heatmap Frequency Index (β = 0.334) and Mean Zone Dwell Time (β = 0.316) follow as the second and third strongest predictors. All nine predictors are statistically significant (all $p < 0.05$), and all VIF values are below 5, confirming the absence of multicollinearity.

The positive and significant beta coefficients for all three clustering variables — silhouette score (β = 0.512), within-cluster dwell variance (β = 0.221), and cluster count (β = 0.142) — collectively and unambiguously reject the null hypothesis and support the alternative hypothesis that a significant positive relationship exists between movement pattern clustering and shopper flow efficiency.

7. Findings And Discussion

1. Key Research Outcomes

The present study confirms that customer movement pattern clustering is a significant and powerful positive predictor of shopper flow efficiency. The full regression model explains 71.4% of SFE variance (R^2 = 0.714; $F(9,190) = 22.67$, $p < 0.001$), with cluster silhouette score emerging as the dominant predictor (β = 0.512, $p < 0.001$). The independent samples t-test demonstrates a 19.5-point SFE differential between high- and low-quality clustering stores — a practically significant gap representing approximately one full standard deviation of the SFE distribution and carrying considerable commercial implications.

A central finding lies in the distinction between the presence of sensing infrastructure and the quality of movement cluster analysis derived from it. Many retailers have invested in sensing technology, but the evidence from this study suggests that analytical rigour — specifically the rigour of clustering methodology — is the decisive factor in determining whether layout improvements are achieved. Retailers appear to benefit not merely from having movement data but from applying analytically rigorous clustering approaches that generate well-differentiated shopper archetypes.

Table 10: Summary of Hypothesis Testing Results
Hypothesis Statistical Test Key Statistic p-value Decision

Hypothesis	Statistical Test	Key Statistic	p-value	Decision
H_0: No significant relationship between clustering and SFE	Pearson r; Regression; t- test	r = 0.81; F = 22.67; t = 8.743	< 0.001	REJECTED
H_1: Significant positive relationship between clustering and SFE	Pearson r; Regression β; t-test	β = 0.512; R^2 = 0.714; MD = 19.5	< 0.001	SUPPORTED

H_0: No significant relationship between clustering and SFE Pearson r; Regression; t- test r = 0.81; F = 22.67; t = 8.743
< 0.001
REJECTED
H_1: Significant positive relationship between clustering and SFE Pearson r; Regression β; t-test β = 0.512; R^2 = 0.714; MD = 19.5
< 0.001
SUPPORTED

2. Theoretical Implications

The study contributes to Environmental Psychology Theory by extending the S–O–R framework's application to the analytics-informed optimisation context. The finding that cluster quality (silhouette score β = 0.512) dominates cluster quantity (K, β = 0.142) challenges the common assumption that 'more granular is better.' The evidence supports an insight aligned with information theory: well-differentiated, internally coherent archetypes provide more actionable layout design signals than a proliferation of poorly separated clusters.

The study strengthens the empirical validation of Space Syntax Theory (Hillier & Hanson, 1984) in a multi-format, cross-regional context. The significant positive effect of aisle integration index on SFE (β = 0.263, $p < 0.001$) confirms that the spatial syntax of retail environments is a consistent SFE predictor across grocery, fashion, electronics, and mixed formats. The finding that planogram compliance (β = 0.219, p = 0.002) significantly predicts SFE reinforces organisational execution theories, suggesting that the 'design-execution gap' has measurable navigational consequences.

3. Managerial Implications

The most important practical implication is the need to shift focus from data collection infrastructure to analytical methodology quality. The evidence suggests that investing in advanced clustering algorithms (DBSCAN, spectral clustering, hierarchical agglomerative methods) targeting silhouette scores ≥ 0.65 yields substantially better SFE outcomes than defaulting to basic k-means implementations. The 19.5-point SFE differential provides compelling ROI justification for this analytical upgrade.

Planogram compliance emerges as a critical execution-level management priority (β = 0.219). Retailers should deploy real-time shelf compliance monitoring tools — such as computer vision-based shelf audit systems — to bridge the design-execution gap. Heatmap-informed zone rebalancing (β = 0.334) represents another high-priority action: quarterly heatmap audits using existing sensing infrastructure can identify persistent cold zones adjacent to high-traffic arteries, with category repositioning interventions potentially increasing zone traffic density by 28–45%.

The absence of geographic differences in the cluster–SFE relationship (ANOVA, p = 0.396) provides an important signal for global retail operators: the Movement–Layout–Clustering model is broadly applicable across geographic markets, allowing centralised analytics infrastructure to be developed once and deployed globally without substantial local customisation of the clustering methodology itself.

8. Limitations Of The Study

While the study provides meaningful insights, certain limitations must be acknowledged. First, the reliance on secondary data introduces measurement heterogeneity, as variable values extracted from different studies were measured using different sensor technologies (CCTV, Wi-Fi, UWB, RFID), each carrying different accuracy and coverage specifications. This heterogeneity introduces noise into the synthesised dataset, potentially attenuating true correlation magnitudes.

Second, the synthesised dataset is somewhat dominated by North American and Western European retail contexts (58.0% of observations), which may limit representativeness for emerging market retail environments in South Asia, Sub-Saharan Africa, or Latin America, where store formats, technology adoption rates, and shopper behaviour profiles differ substantially.

Third, the cross-sectional nature of the secondary data precludes longitudinal causal inference. High-performing stores may invest more in analytics because of their performance orientation, rather than clustering-informed layouts causing higher SFE. Fourth, the SFE Composite Index, while synthesised from validated sub-dimensions, is not a universally standardised construct, potentially limiting comparability across source studies.

IX. CONCLUSION

This study set out to examine the relationship between customer movement pattern clustering and shopper flow efficiency in retail store environments, using a comprehensive secondary data synthesis of 200 store observations drawn from 47 qualifying sources. The findings confirm that customer movement pattern clustering is a significant and powerful positive predictor of shopper flow efficiency, with the full model explaining 71.4% of SFE variance. The null hypothesis (H_0) is definitively rejected at $p < 0.001$, and the alternative hypothesis (H_1) is strongly supported across all analytical approaches employed.

A key conclusion is that the effectiveness of movement pattern clustering lies not merely in its existence but in its quality. Retailers who invest in high-quality clustering algorithms producing well- separated, internally coherent shopper archetypes achieve systematically superior SFE outcomes — as demonstrated by the 19.5-point SFE differential between high- and low-silhouette-score stores. This places the emphasis squarely on analytical rigour rather than data volume as the primary differentiator of layout optimisation success.

The study also highlights that SFE is shaped more by analytical methodology and operational execution quality than by geographic or contextual factors. This reinforces that retail management practitioners have substantial internal control over SFE outcomes through analytical investment and execution discipline. By prioritising clustering quality, spatial integration, and planogram compliance as the three pillars of their layout analytics strategy, retail organisations can create environments where customers navigate efficiently, engage productively with merchandise, and convert at higher rates — generating measurable commercial returns from their analytical investments.

1. Scope for Future Research

The present study opens several avenues for future research. First, validation of the Movement– Layout–Clustering (MLC) Model through a primary data collection study employing standardised UWB tracking across a stratified sample of 50+ stores with pre- and post-layout-redesign measurement periods would enable causal attribution and longitudinal SFE impact measurement. Second, research should extend across South Asian, African, and Latin American retail environments to examine whether the cluster–SFE relationship magnitude varies across cultural contexts.

Third, the exploration of real-time dynamic layout optimisation — utilising LSTM-based predictive trajectory models and reinforcement learning frameworks — represents the frontier of retail analytics research. Fourth, future studies should examine moderating variables, particularly store staff density, ambient atmospheric conditions, digital signage placement, and technology implementation quality, in the cluster–SFE relationship to provide more nuanced practical guidance.

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