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MICRO-SCALE SPATIAL MODIFICATION AND PEDESTRIAN BEHAVIOR

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Abstract. This paper proposes a flexible framework for hypothesis testing of behavioral changes in pedestrians in field environments and provides a case study demonstrating its application. The framework employs computer-vision-based 3D tracking using existing CCTV networks to collect uncontrolled, ecological data of pedestrian movement and extracts the nature and duration of pedestrian behaviors without prior assumptions. To evaluate the framework, we conducted a case study in a specialty retailer where, after collecting control data, pedestrian flow was intentionally constricted by introducing in-aisle obstacles. We observed a marked rise in traversal and navigation of the aisle accompanied by reductions in browsing and deliberation. We conclude that this framework offers utility in optimizing retail environments and can be generalized to model the effects of environmental changes on behavior in spaces where loitering, dwell time, or free flow of traffic are relevant design considerations.

Keywords: Pedestrian behavior, Spatial design, Machine vision, Behavior classification.

1. Introduction

Understanding how the design of physical environments shapes human movement and decision-making is a central question in both applied and theoretical research on pedestrian dynamics.

1.1. Motivation

The ability of spatial design to shape pedestrian behavior has drawn considerable public and scholarly attention over recent decades [1–5]. Despite the important ethical and practical ramifications of this area of research, there remains a dearth of methods to quantify, model, and test the impact of spatial alterations on pedestrian behavior [6]. For clarity of discussion, it is useful to informally group research in pedestrian dynamics into three broad methodological domains (following categorization influenced by [7]):

(1.) Modeling individual pedestrian movement across varying densities.

(2.) Modeling collective or crowd movement at high densities.

(3.) Examining how environmental changes influence pedestrian behavior, particularly path selection.

The concentration of work in the first two domains reflects not only the critical importance of safety-related applications but also the practical constraints of existing research tools. Person-counting and path-tracking approaches are comparatively straightforward to deploy and validate, whereas capturing fine-grained, unscripted behaviors in natural environments, including semi-structured indoor settings such as retail spaces – where environmental influences on pathing have drawn significant attention [8–10] – remains technically and logistically challenging.

Many environmental modifications in real-world settings do not elicit large or immediately observable behavioral shifts, as evidenced by the literature on behavioral nudging—which further illustrates the difficulty of detecting subtle or distributed behavioral changes across populations [11]. As a result, design decisions outside of regulatory mandates often rely more on architectural intuition, established conventions, and cost considerations than on the type of rigorous, data-driven experimentation that characterizes digital user experience (UX) research. Expanding the empirical reach of pedestrian studies therefore requires more sensitive observational and analytical tools capable of detecting nuanced behavioral variation in response to environmental design.

In response to these limitations, this paper introduces a methodological and technical framework for testing how physical environmental changes influence pedestrian behavior, and demonstrates its use through a case study centered on a controlled field experiment implemented in collaboration with a US-based specialty retailer.

1.2. Contributions

This paper makes two primary contributions to the field of pedestrian dynamics.

First, it introduces a methodological and technical framework for conducting controlled field studies that measure subtle and complex changes in pedestrian behavior resulting from modifications to the built environment. The framework integrates advances in pose-based 3D tracking, trajectory segmentation, and unsupervised behavioral modeling into a unified process for hypothesis testing in naturalistic settings. This contribution is both methodological and technical in nature; providing both a systematic approach for behavioral experimentation in the wild and demonstrating a scalable architecture that operates on existing CCTV infrastructure. Together, these elements enable researchers and practitioners to quantify behavioral effects that have traditionally been observable only in highly instrumented laboratory environments.

Second, we present a case study centered on a controlled field experiment implemented in collaboration with a US-based specialty retailer. The seven-week study evaluates the behavioral impact of in-aisle promotional shelving, testing a long-standing assumption in retail design. While uncovering new behavioral phenomena is not the primary aim of this work, the case study demonstrates the framework's ability to detect and statistically evaluate subtle but important behavioral shifts in uncontrolled, real-world conditions.

Broadly, this work advances the empirical and technical capacity of pedestrian dynamics by bridging experimental rigor with practical deployability, offering a pathway to study how environmental design choices shape human behavior at scale.

2. Methodological Framework

This section outlines both the conceptual design and practical implementation of a generalizable framework for testing how changes in physical environments influence pedestrian behavior. The framework is adaptable across contexts, scalable to real-world environments, and independent of any specific computer vision or machine learning pipeline. It is organized into two complementary components: the **Conceptual Framework**, which defines the logic and structure of the method, and the **Implementation**, which describes the specific algorithms and data processing techniques used in our controlled field experiment.

2.1. Conceptual Framework

At its core, the framework transforms raw multi-camera video streams into interpretable measures of behavioral change through a structured sequence of automated and human-in-the-loop steps. Each stage serves a distinct conceptual role:

- **Observation.** Using existing multi-camera or CCTV infrastructure, the system captures pedestrian motion at sufficient temporal and spatial resolution to reconstruct trajectories without instrumenting participants or altering their behavior.
- **Representation.** Multi-view geometry and pose estimation are used to convert raw imagery into three-dimensional trajectories: continuous physical records of movement through space and time.
- **Segmentation.** These trajectories are divided into behaviorally homogeneous intervals using an unsupervised process that detects changes in movement dynamics. Each segment represents a single behavioral episode in the physical sense defined above.
- **Abstraction.** Each behavioral segment is transformed into a compact representation, or embedding, that captures its intrinsic temporal and geometric characteristics.
- **Aggregation.** Segments with similar embeddings are grouped into clusters, yielding recurring patterns of motion that constitute the empirical basis for behavioral classes.
- **Interpretation.** Human reviewers label a limited number of representative samples from each cluster with high-level behavioral attributes of interest. These annotations anchor the unsupervised model in human-understandable semantics.
- **Comparison.** Finally, the distribution of behavioral clusters is compared across experimental conditions (e.g., before and after a spatial modification) to test hypotheses about how changes to the environment influence pedestrian behavior.

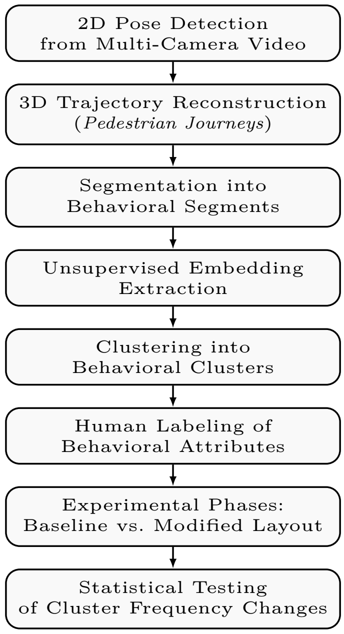

FIGURE 1. Conceptual overview of the methodological framework. The process transforms raw video data into behavioral representations and enables hypothesis testing on how spatial modifications influence pedestrian behavior.

Together, these stages define a generalizable process for observing, representing, and statistically testing behavioral change in naturalistic settings. The framework is designed to be modular and scalable for large environments where controlled experiments are otherwise infeasible, allowing substitution of alternative vision, embedding, or clustering algorithms in diverse environments. In the following section, we describe the specific algorithms and data processing techniques used to implement this framework in our field experiment.

2.2. Specifically Addressed Conceptual Challenges

Unlike in laboratory settings, pedestrian motion in natural environments is continuous, unstructured, and often driven by implicit intent rather than observable goals. This makes it difficult to define where one behavior ends and another begins, or to specify the full set of behaviors a pedestrian might exhibit. In practice, the act of defining, selecting, and categorizing behaviors introduces human bias and limits generalization. Measuring behavioral change requires addressing specific critical problems, such as:

(1.) **Behavioral Definition.**
- (a) What constitutes a behavior?
- (b) What marks the start and end of a behavior?

(2.) **Behavioral Selection.**
- (a) What are all of the behaviors a pedestrian can engage in?
- (b) Which of those behaviors are relevant to the testing environment?

(3.) **Behavioral Extraction.**
- (a) How can behavioral occurrences be captured and categorized?
- (b) How can this be done at sufficient scale and reasonable cost?

Our framework attempts to resolve the difficult questions of definition and selection by redefining behavior in operational rather than semantic terms and, by doing so, elide the question of selection to the greatest possible extent. We treat "behaviors" as nothing more than processes that exhibit internal continuity and self-similarity while also displaying external discontinuity and dissimilarity. This perspective eliminates the need to predefine behavioral categories and instead allows them to emerge empirically from observed motion. We also make a categorical differentiation between behaviors and their attributes: while behaviors are ineffable and latent, their attributes can be binary, classifiable, and contribute to understanding the emergent behavioral classes.

2.3. Implementation

The conceptual framework was operationalized using a combination of computer-vision, statistical, and human-in-the-loop processes designed to transform raw multi-camera video data into interpretable behavioral metrics. While the specific implementation described here was developed in collaboration with Standard AI and makes use of proprietary systems, all processing stages can be reproduced using open-source alternatives.

2.3.1. Pose Estimation and 3D Trajectory Reconstruction

Video data from multiple overlapping cameras were first processed using pose-estimation models to extract two-dimensional joint locations for each visible individual in image space. These detections were temporally linked within each camera view and then triangulated across cameras to produce three-dimensional pedestrian trajectories, hereafter referred to as "pedestrian journeys."

Recent advances in markerless motion capture have shown that pose-based methods can achieve near–motion-capture accuracy using only multi-camera or CCTV setups [12, 13]. Following a similar approach, the system leverages synchronized video inputs from existing overhead and fixed-angle cameras to reconstruct continuous 3D trajectories without instrumenting participants. Each trajectory is represented as a time-ordered series of keypoints describing the spatial coordinates of the head, torso, and lower limbs at 10 Hz.

2.3.2. Trajectory Smoothing and Behavioral Segmentation

Reconstructed trajectories were filtered using a fourth-order Butterworth low-pass filter to suppress high-frequency noise and mitigate pose jitter caused by occlusions or short-term estimation errors. The smoothed trajectories were then segmented into behaviorally consistent intervals using an unsupervised changepoint detection algorithm [14]. This method identifies points of transition in motion dynamics by examining temporal discontinuities in the derivatives of position and orientation. This segmentation process operationalizes the definition of "behavior" described in Section 2.1: each segment represents a period of self-similar movement bounded by points of discontinuity, independent of any predefined behavioral taxonomy. Segments are interpolated to a constant temporal length and normalized by total displacement to ensure that subsequent comparisons reflect behavioral structure rather than individual differences in speed or physical ability. The overall effect is of partitioning each trajectory into sequences of internally coherent motion.

2.3.3. Behavioral Embedding and Clustering

Each normalized segment is transformed into a low-dimensional embedding using multi-functional principal components analysis (MFPCA). MFPCA models the trajectories and their derivatives such as velocity and angular velocity as continuous functions and projects them onto a set of orthogonal basis functions that capture the principal modes of variation across all segments. This approach (similar to [15]) yields a compact, unsupervised representation of motion dynamics that captures the most informative axes of behavioral differentiation.

The resulting embeddings are clustered using k-means to identify recurring patterns of motion. Cluster membership reflects the proximity of behavioral segments in the embedded space; segments grouped together exhibit kinematic signatures most explicable by similar functional mechanisms, or from another perspective, permit the highest degree of reconstruction of the original pedestrian motion. These clusters form the empirical basis for defining behavior classes in a data-driven manner, as the rates at which various pedestrian activities occur vary substantially between clusters, as seen below.

2.3.4. Human Labeling and Attribute Calibration

To facilitate interpretation and ensure methodological validation, a sample of segments from each behavioral cluster were reviewed by trained human annotators. Labelers assigned binary behavioral attributes such as traversal, browsing, deliberation, or item interaction, according to a predefined taxonomy relevant to retail contexts. These attributes serve as interpretable proxies for latent behavioral modes. By aggregating attribute frequencies within clusters, we establish a mapping between unsupervised cluster identities and human-interpretable behaviors. Statistical hypothesis testing may be performed on cluster frequencies without this baseline, but establishing the baseline permits researchers to validate the inherent logic in the suggested direction of behavioral change and explain the consequences of such a change in concrete terms.

Together, these stages constitute an end-to-end system for detecting, representing, and quantifying behavioral change in naturalistic environments. The framework's modular structure allows each component to be substituted or extended in line with particular requirements or technological advances. In the following section, we demonstrate the framework's application through a controlled field experiment conducted in a retail environment.

3. Case Study: Retail Application

This section presents a case study demonstrating the application of the proposed framework to a real-world retail environment. The goal is to validate the framework's ability to detect and interpret behavioral changes resulting from a controlled modification to a store's physical layout. In collaboration with a US-based specialty retailer, we conducted a field experiment designed to assess how changes in aisle geometry influence pedestrian movement and browsing behavior.

3.1. Context

Physical retailers test the success of in-store changes through reference to store transactions. The complex nature of retail environments, where sales are influenced by numerous outside factors makes it difficult for even sophisticated sales-based analysis to attribute changes in sales to in-store experimentation.

The prevalence of promotional in-aisle shelves across retailers has increased in recent decades. While experimentation is difficult, industry wide trends such as this typically have been shown to positively impact sales and profitability, and this change has an inherent logic as promotional shelves increase the viewable area within an aisle in the same amount of physical space by introducing folds to the previously flat shelf.

However, this generally positive direction of effect does not mean that promotional shelves have been implemented in a way which is ubiquitously positive or optimized. Retailers have been moving toward very high counts of promotional shelves in each aisle, with the expectation of continued positive marginal returns. Existing research such as [16, 17] offered us reason to believe that desirable pedestrian behaviors do not simply scale linearly with the count of promotional shelves and that the particular details of implementation are significant.

3.2. Experimental Design

The study was conducted over a seven-week period in a specialty retailer's store aisle. Data collection leveraged a commercial vision-based analytics platform developed by Standard AI, deployed on the retailer's pre-existing overhead security camera infrastructure. Finetuned 2D pose detection models, each operating at 10 FPS, generated multi-view detections that were triangulated into 3D pedestrian trajectories, enabling continuous observation of natural shopper behavior without direct intervention.

During the first four weeks (the baseline phase), pedestrian activity was recorded under normal layout conditions. After week four, the retailer introduced an intervention consistent with its established merchandising principles: the addition of promotional shelving units along the aisle's south side, previously unoccupied by such fixtures. This change reduced the navigable width from approximately 2.5 m to 1.7 m, producing a situationally plausible but physically significant constriction. The intended design goal was to encourage traversal-oriented movement by subtly reducing the space available for browsing. The subsequent four weeks (the intervention phase) were observed under this modified configuration. No other layout, pricing, or promotional changes occurred during this period.

3.3. Rationale and Hypothesis

While promotional shelves are widely used in retail to increase product exposure and sales, their behavioral effects are rarely isolated or quantified. Prior studies in pedestrian dynamics suggest that spatial constriction may suppress browsing behavior by channeling movement along narrower, more linear trajectories [18, 19]. However, empirical verification of such effects in real-world environments remains limited.

Intuition derived from the social force model guided our thinking in devising a pedestrian experiment in a retail environment which would be more successful in challenging existing retailer assumptions about spatial layout, though a rigorous examination was not pursued. As such we briefly detail a sketch of the

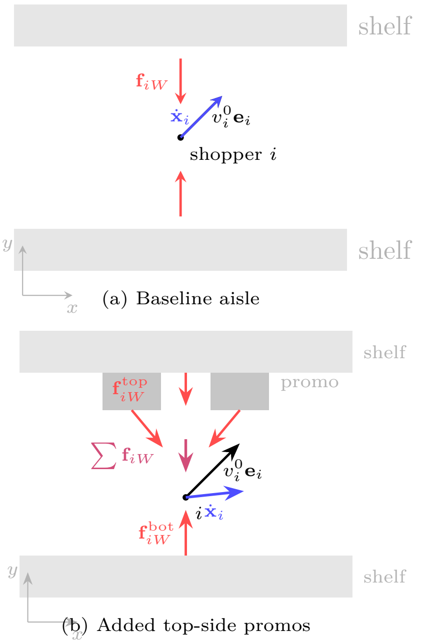

FIGURE 2. One possible consequence of a social-force baseline in a shelf aisle: (b) symmetric top-side promos raise repulsion on that side, pushing the shopper away and yielding more shelf-parallel motion.

way that the social force model guided our thinking in approaching the experimental design.

We use a standard social-force formulation [20, 21]. For pedestrian i (mass m_i; position $\mathbf{x}_i$; velocity $\mathbf{v}_i$):

$$m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{v_i^0\,\mathbf{e}_i - \mathbf{v}_i}{\tau_i} + \sum_{j\neq i} \mathbf{f}_{ij} + \sum_{W} \mathbf{f}_{iW}.$$

$v_i^0\mathbf{e}_i$ is the desired velocity. $\mathbf{f}_{ij}$ are pedestrian repulsions. $\mathbf{f}_{iW}$ are wall/fixture repulsions. A common repulsive form is $\mathbf{f}_{ij} = A\exp\left(\frac{r_{ij}-d_{ij}}{B}\right)\mathbf{n}_{ij}$, with d_{ij} distance, r_{ij} sum of radii, and $\mathbf{n}_{ij}$ the normal from j to i. Similar terms apply for $\mathbf{f}_{iW}$. Although likely too simple to describe, in a quantitative way, human navigation in a complex environment, we deemed this model sufficient for a qualitative understanding of pedestrian behavior in presence of static obstacles.

Implications in a shelf aisle (qualitative): (1) As shelves approach (narrower aisle), $\|\mathbf{f}_{iW}\|$ grows, suppressing the shelf-normal component of motion; paths become more parallel to shelves. This reduces natural, orthogonal viewing opportunities of facings. (2) Added promotional fixtures increase local repulsions (from walls and other shoppers). When placed on the same side as the intended target shelf, symmetric fixtures fore/aft cancel lateral x-components of force and yield a net y (shelf-normal) push *away* from that side, diminishing browsing near promotions.

These sketches motivate our pre-registered hypothesis: **Reduced width from promos on the target side leads to lower orthogonal viewing, which in turn reduces local browsing near promotions.**

From this perspective, we hypothesized that narrowing the aisle would reduce browsing and deliberation behaviors, while increasing traversal and navigational activity. This effect would be detectable as a redistribution of behavioral cluster frequencies under the proposed framework. The null hypothesis of this test was that the frequency of the occurrence of behavioral clusters would prove unchanged between the baseline phase and the test.

3.4. DATA COLLECTION AND ANALYSIS

Data were collected continuously over the seven-week study period, encompassing both baseline and intervention phases. Each shopper's movement through the camera coverage area was reconstructed as a 3D trajectory at 10 Hz using triangulated detections from finetuned 2D pose models operating on the retailer's existing overhead security cameras. As detailed in Section 2.1, trajectories were preprocessed, segmented into behaviorally consistent intervals, embedded via multi-functional principal components analysis, and clustered to yield interpretable behavioral categories.

For this case study, we specified that the clustering model should produce 22 distinct behavioral clusters. This number was empirically chosen as a balance between breadth and interpretability: large enough to capture the diversity of micro-behaviors observed in retail settings, yet small enough to permit qualitative validation through manual review of representative trajectory samples. After initial trials with higher and lower cluster counts, 22 was found to yield clusters that were internally cohesive, externally distinct, and qualitatively consistent when cross-checked against synchronized video segments. This step ensured that cluster membership meaningfully described behavior rather than noise or individual differences in physical ability.

To calibrate these clusters with interpretable meaning, we leveraged a pre-existing ground-truth dataset of 2,500 human-labeled behavioral segments drawn from other retail environments. Each segment was annotated with binary indicators for ten action attributes: phone use, shopping cart use, item takes, puts, and touches, traversal, browsing, deliberation, uncertainty, and shelf attention. Averaging these attribute frequencies within each cluster yielded an attribute-rate vector describing the behavioral composition of that cluster.

Aggregating across the full observation window produced hundreds of thousands of behavioral segments. The relative frequency of each behavioral cluster was computed separately for the baseline and intervention periods, forming the input distribution for statistical testing. For completeness, we also examined journey-level structure by grouping sequences of segment-level clusters into a small number of meta-clusters describing whole trips. While these are discussed further in

Section 4, they provided additional context for interpreting how local behavioral changes propagate to the scale of entire shopping journeys.

3.5. Experimental Controls

Field experiments conducted outside of controlled laboratory settings are inherently vulnerable to confounding influences. In retail environments, non-experimental shifts in pedestrian behavior may arise from both *exogenous* factors (e.g., seasonality, advertising, or social media trends) and *endogenous* factors (e.g., changes to layout, product placement, signage, or pricing). Without explicit controls, hypothesis tests risk capturing these effects rather than isolating the impact of the intended intervention.

To mitigate these risks, we partnered with a retailer whose business model and collaboration allowed us to reduce confounding without requiring additional statistical correction. The retailer is a specialized seller of staple goods with exceptionally low seasonality relative to the broader industry. Customers are habituated to purchasing specific brands at time-invariant rates. The core offerings carry high switching costs and the effects of external advertising or other similar stimuli operate on timescales longer than our study window. To further limit potential confounds, the retailer made no layout, promotional, or price changes at the study location during data collection. This stability provided a unique opportunity to isolate behavioral effects attributable solely to the spatial modification.

3.6. Statistical Evaluation

Using the labeled calibration described above, each behavioral cluster has a characteristic vector of attribute rates (e.g., average frequency of browsing or traversal). Let $p_k^{(0)}$ and $p_k^{(1)}$ denote the proportions of segments assigned to cluster k during the baseline and intervention phases. The null hypothesis is that the intervention does not alter the distribution of behavioral clusters:

$$H_0 : \; p_k^{(0)} = p_k^{(1)} \quad \text{for all } k = 1, \ldots, 22.$$

A 22×2 contingency table of cluster frequencies was constructed, and a chi-square test of independence was applied. Standardized residuals identified which clusters contributed most to deviations from the null. Combining these shifts with each cluster's attribute profile enabled estimation of aggregate behavioral change across the study period, revealing how physical alterations in space translated into measurable shifts in pedestrian behavior.

4. Results and Evaluation

This section reports the empirical outcomes of the retail field experiment and assesses how effectively the proposed framework captured and explained those behavioral changes.

4.1. Behavioral Effects of the Intervention

Chi-square analysis revealed statistically significant changes in pedestrian behavior at both the segment and journey levels ($p < 10^{-16}$). As such, we reject the null hypothesis of behavioral stasis after the introduction of pedestrian flow constriction. That the spatial intervention produced a measurable redistribution of behavioral patterns lends credence to the proposed testing framework, especially as these shifts were broadly consistent with expectations derived from the social-force model and prior research in constrained pedestrian dynamics, though they diverged from the retailer's initial assumptions.

At the segment level, most of the 22 behavioral clusters decreased in relative frequency, while five clusters occurred 10% or more frequently. Cluster 8, already a common behavioral mode, exhibited a 33% increase in occurrence following the intervention and contributed more than half of the total chi-square test statistic (Fig. 3). This cluster was characterized by continuous forward motion with minimal shelf engagement; behavior characterizable as traversal rather than browsing. While individual cluster-level significance cannot be directly inferred in a multi-category test, the aggregate pattern indicates that behaviors associated with engagement decreased while those associated with transit increased.

When the cluster membership migrations are mapped onto human-labeled behavioral attributes (Fig. 4), this shift manifests as a marked increase in the rate of the "exclusive traversal" attribute. These segments were ones in which shoppers moved through the aisle without attending to the shelves. Attributes indicating any degree of mental or physical engagement with the environment (e.g., browsing, deliberation, item interaction) declined in frequency, while "uncertainty" rose slightly. In essence, shoppers engaged less frequently in exploratory or deliberative behaviors and were more likely to treat the aisle as a passageway. This lends additional credence to the formal hypothesis testing conducted above.

As well as at the segment level, the constriction produced statistically significant and consistent results at the journey level, indicating that the constriction can alter entire trips, not just brief segments. The prevalence of trip-level clusters 0, 3, and 4 increased, while clusters 1 and 2—those associated with higher browsing and item-interaction rates—declined (Fig. 3). Qualitative review of video samples confirmed a shift toward more linear, goal-directed movement with reduced spatial exploration.

Overall, the findings indicate that narrowing the aisle through added promotional shelving suppressed behaviors associated with product engagement and increased direct traversal, consistent with the hypothesis that physical constriction elevates repulsive social forces and reduces opportunities for orthogonal (shelf-normal) movement.

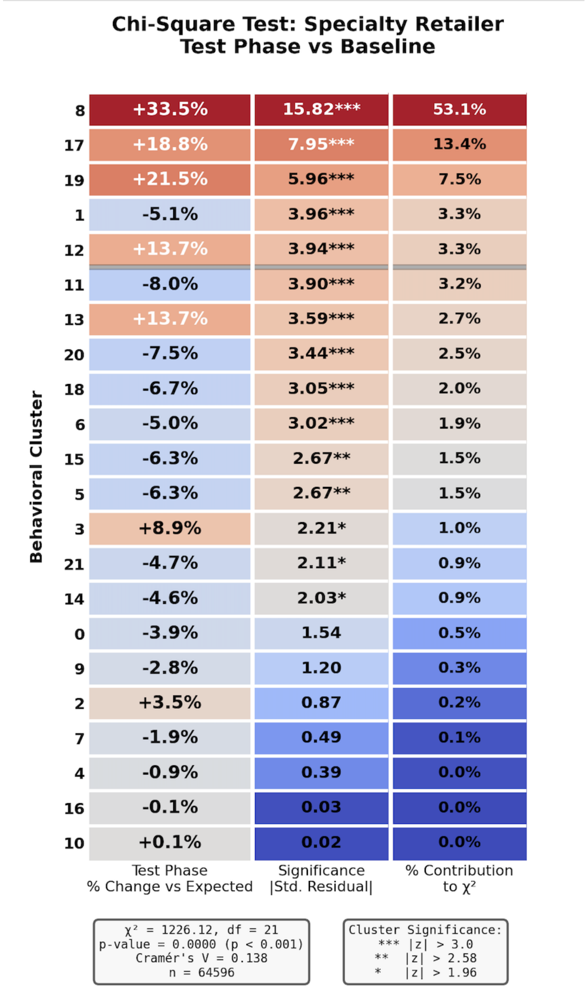

FIGURE 3. Chi-square contributions of behavioral clusters before and after intervention. Cluster 8, representing traversing behaviors, dominates the overall test statistic.

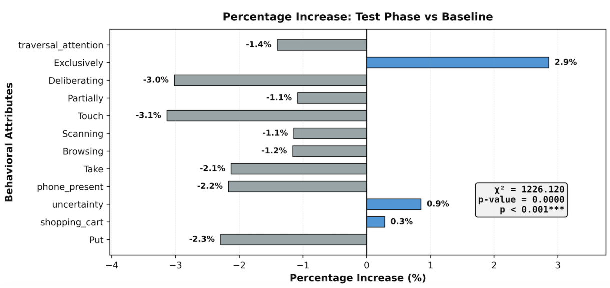

FIGURE 4. Change in attribute-level behavioral frequencies following intervention. Traversal increased, while browsing and item interaction decreased.

4.2. Framework Performance and Validation

The case study also served as a practical validation of the proposed analytical framework. The combination of multi-camera 3D tracking, behavioral segmentation, and unsupervised clustering successfully detected nuanced shifts in shopper behavior without any manual intervention during data collection. The resulting behavioral clusters demonstrated internal consistency and interpretability: visual inspection of representative segments confirmed that members of the same cluster exhibited coherent motion patterns.

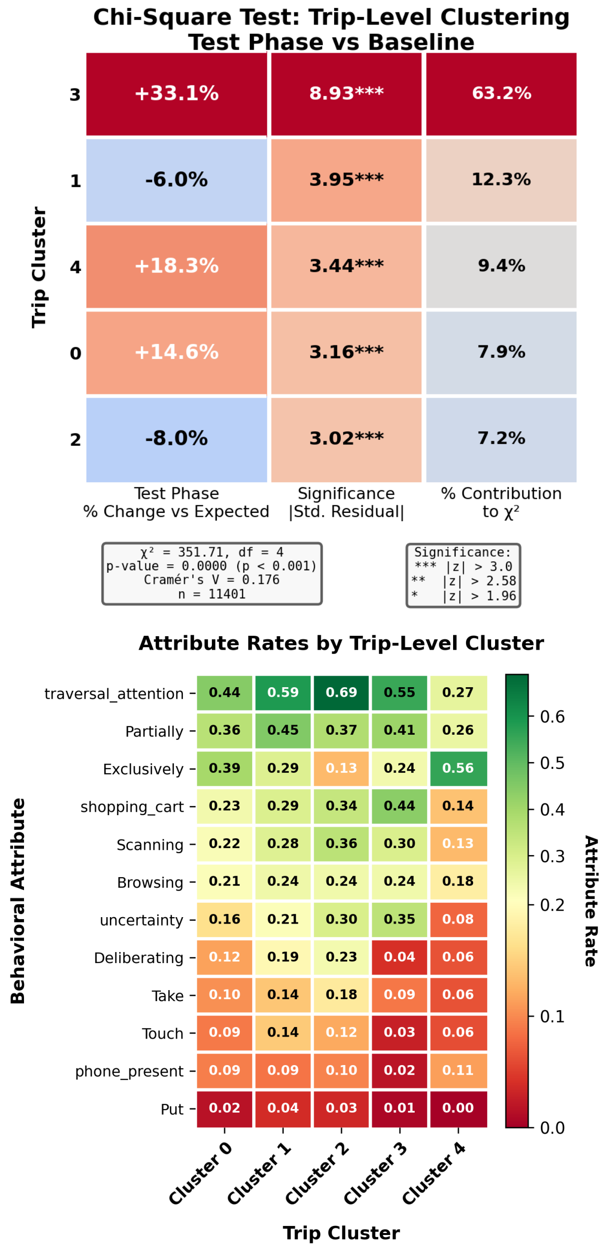

FIGURE 5. (Top) Chi-square analysis of journey-level clusters. (Bottom) Corresponding attribute-rate profiles show reduced browsing and deliberation in post-intervention trips.

The framework's sensitivity to subtle, population-level changes was evident in its ability to capture a redistribution of behavioral modes in response to an environmental modification that would likely go unnoticed by traditional retail analytics, which typically rely on aggregate sales or dwell-time proxies. The experimental design of baseline and treatment phases enabled statistical validation through standard inferential tests, avoiding the need for ad hoc heuristics or subjective interpretation. The overwhelming strength of the significance detected in the chi-square analysis points to the possibility of shortened testing phases, allowing for testing that further reduces the influence of confounders.

These findings show that modest spatial modifications can exert outsized influence on pedestrian dynamics, even at low densities, and highlight the value of micro-scale analysis for retail and urban planning alike. The framework can generalize to other contexts: public seating placement, signage efficacy in transport hubs, or balancing dwell time with circulation in museum galleries [3, 11]. By coupling high-resolution trajectory tracking, behavioral segmentation, and controlled spatial interventions, this study offers a reproducible, data-driven lens on how design nudges pedestrian behavior. Beyond retail, such methods enrich pedestrian- and evacuation-dynamics research by enabling quantitative tests of spatial design.

From a practical perspective, the framework operated entirely on existing CCTV infrastructure, requiring no additional instrumentation or human observation, and processed data at near–real-time rates. While the labeled attributes enhanced our understanding of the behavioral clusters, these labels were required only for interpretability; the framework still enables hypothesis testing without prior domain knowledge. This demonstrates its feasibility for broader deployment in dynamic environments where behavioral validation would otherwise be costly or impractical.

4.3. Discussion and Broader Implications

The results are intuitively consistent and empirically significant, challenging prevailing assumptions within retail design. The intervention's effect of dampened browsing and deliberation while increasing straightforward traversal suggests that excessive in-aisle fixtures may impose cognitive and physical friction that discourages exploratory movement.

While the findings do not refute the long-standing assumption that promotional shelves have a positive marginal impact on sales, they reveal a more complex relationship between the inclusion of in-aisle displays and shopper behavior, suggesting that the point at which their marginal returns become negative may occur earlier than previously believed. Further, these results highlight the power of micro-scale spatial design to shape pedestrian dynamics, even in low-density environments such as retail aisles.

Methodologically, the study demonstrates the value of integrating computer-vision–based behavioral segmentation with experimental design principles traditionally reserved for controlled laboratory settings. The ability to detect fine-grained, unsupervised behavioral shifts in real-world environments bridges the gap between simulation-driven pedestrian modeling and in-situ validation.

Beyond retail, the framework can extend to other spatial domains, including evaluating how urban design interventions affect enjoyment of public places or how signage placement influences navigation in transportation hubs. By offering a scalable, data-driven means to quantify behavioral response, this approach provides a foundation for empirical testing of environmental design hypotheses across disciplines.

Finally, while this case study relied on proprietary 3D pose estimation software, implementation of this framework is not reliant on a particular specification of any of the particular steps, and could be replicated using open-source alternatives for pose detection and multi-view reconstruction.

5. Conclusion

This study introduced and demonstrated a methodological framework for empirically testing how changes to the built environment influence pedestrian behavior in naturalistic settings. By integrating pose-based multi-camera tracking, unsupervised behavioral segmentation, and statistical hypothesis testing, the framework enables rigorous, data-driven experimentation outside of controlled laboratory conditions.

Through its application in a real-world retail context, we showed that even modest spatial modifications, such as adding in-aisle promotional shelving, can produce measurable and interpretable shifts in pedestrian behavior. The case study confirmed that spatial constriction reduces browsing and deliberation while increasing direct traversal, highlighting how subtle design interventions can meaningfully alter movement dynamics and engagement patterns.

Beyond its immediate empirical findings, this work demonstrates that high-fidelity computer vision and unsupervised analytics can bridge the gap between traditional simulation-based pedestrian modeling and field-based behavioral validation. The approach offers researchers and practitioners a scalable means of quantifying behavioral responses to design changes, using only existing camera infrastructure and minimal manual supervision.

Future work will extend this framework across domains and scales—from retail environments to transportation hubs and public spaces—and refine its behavioral taxonomy and statistical inference methods. More broadly, the framework provides a foundation for connecting spatial design and human behavior through reproducible, experiment-based evidence, advancing both the methodological and applied frontiers of pedestrian dynamics.

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