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Generative AI Meets Cross-Brand Fit Intelligence: A User-Centric Framework for Outfit Recommendation with Occasion and Weather Awareness

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Abstract- Online fashion retail suffers from inconsistent sizing across brands and difficulty in composing context-appropriate outfits. Existing recommender systems address either fit or style, but not both in an integrated manner. We present FitGen, a generative AI framework that combines cross-brand size intelli-gence with occasion- and weather-aware outfit recommendation. FitGen collects user body measurements and style preferences, maps them to brand-specific sizes using a weighted Euclidean distance heuristic, and generates personalized outfit descriptions via GPT-4o-mini and corresponding visualizations via DALL-E-3. All interactions occur within a privacy-first Streamlit dashboard. A controlled user study (N=100) demonstrates that FitGen achieves 78.3% fit accuracy across five brands, with precision and recall values of 0.79 and 0.78 respectively, a 4.6/5 user satisfaction score, and a 92% reduction in self-reported size anxiety. The end-to-end latency is 3.2 seconds. We compare our results with existing commercial solutions and academic models, highlighting the trade-offs between transparency and accuracy. While limitations exist, including synthetic measurement distributions, a heuristic size mapper, and the absence of live e-commerce APIs, the results indicate that combining generative AI with explicit fit modeling significantly enhances the online fashion shopping experience. The prototype, source code, and a demo video are made publicly available to facilitate further research.

Keywords— Generative AI, Fashion Recommendation, Cross-Brand Sizing, Large Language Models, Text-to-Image, Personalization, Streamlit.

I. INTRODUCTION

The global online fashion market is projected to reach $1.2 trillion by 2027, yet return rates remain persistently high, ranging from 24% to 40%, with "poor fit" being the primary driver [1]. Unlike physical stores, e-commerce forces shoppers to rely on generic size charts and static images, leading to a disconnect between expectation and reality. This problem is exacerbated by a lack of sizing standardization across brands: a "size M" from one label can correspond to vastly different body measurements, creating significant consumer friction [2]. Beyond fit, consumers often struggle to assemble complete outfits that are not only stylish but also appropriate for a specific occasion and weather condition, a gap that purely visual or collaborative filtering recommenders fail to address.

Existing fashion recommendation systems typically fall into three silos: collaborative filtering [4], content-based visual matching [5], and more recently, generative AI for styling [7]. While each has its merits, they are fundamentally disconnected. Commercial tools like TrueFit offer size recommendations but operate independently of any outfit styling logic. Conversely, emerging generative stylists, such as those built on Large Language Models (LLMs), can suggest cohesive looks but lack any awareness of the user's physical body or brand-specific sizing. This creates a fragmented user experience where the critical "will it fit?" and "will it look good together?" questions are answered by separate systems, if at all.

We introduce FitGen, a unified AI framework designed to bridge this gap between generative styling and cross-brand fit intelligence. FitGen is built on a user-centric pipeline that starts with body measurements and style preferences to deliver a complete, personalized outfit recommendation, including the correct size for each garment and a realistic visualization. Our key innovation lies in the tight integration of a transparent, weight-aware size mapper with a generative AI pipeline, creating a system that is both explainable and personalized—a combination absent from current commercial or academic tools. Our contributions are:

A novel Cross-Brand Size Mapping Engine that translates user body measurements (chest, waist, hips, inseam) into a recommended size for any given brand using a weighted Euclidean distance heuristic, addressing the problem of sizing inconsistency directly.

A Multi-Agent Generative AI Pipeline where an LLM produces a structured, context-aware outfit description (conditioned on style, occasion, and weather), and a text-to-image (T2I) model visualizes this outfit on a body-proportional model.

An Interactive Streamlit Dashboard that provides a privacy-first onboarding experience, visual size compari-son charts, and a history of recommendations, making the AI's decision-making transparent to the user.

A Controlled User Study (N=100) that rigorously evaluates FitGen, demonstrating 78.3% cross-brand fit accuracy, precision/recall of 0.79/0.78, a 4.6/5 user satisfaction score, and a 92% reduction in size anxiety compared to a brand-agnostic baseline.

We acknowledge that FitGen is a proof-of-concept with a rule-based size mapper and no live e-commerce integration, yet the positive results underscore the transformative potential of tightly coupling generative AI with explicit, user-aware fit modeling.

II. RELATED WORK

1. Fashion Recommendation Systems

Early fashion recommenders heavily relied on collaborative filtering [4], which suffers from the cold-start problem and fails to capture the visual subtleties of fashion items. Content-based methods using CNNs for visual similarity improved on this by recommending visually compatible items [5], but they often lack a holistic view of an outfit. More advanced graph neural networks model pairwise compatibility between fashion items to create a cohesive look [6], yet none of these approaches incorporate the crucial dimension of physical fit or user body measurements. They answer "what goes with what" but not "what fits whom." This is where our work fundamentally differs, integrating fit into the style recommendation loop.

2. Generative AI for Styling

The emergence of LLMs and diffusion models has opened new avenues for generative fashion applications. Fash-ionGPT [7] leverages the conversational and reasoning abilities of LLMs to generate detailed outfit descriptions from natural language prompts. Similarly, OutfitDiffusion [8] uses text-to-image models to create visual representations of complete outfits. However, these systems operate in a purely abstract, style-only dimension. They assume a generic body shape and have no mechanism to recommend a size or understand how an outfit would look on a specific individual. FitGen is the first, to our knowledge, to jointly optimize for both style (using GenAI) and physical fit (via an explicit size mapping engine), thus creating a recommendation that is both aesthetically pleasing and practically wearable.

3. Size and Fit Prediction

Accurate size prediction is a multi-million dollar problem, with commercial solutions like TrueFit and Fit Analytics dominating the market. These systems often require vast datasets of purchase and returns history to build their models. In academia, models like FitPredictor [9] use multi-task learning on purchase data to predict fit, but such data is rarely public. Recent work by [10] uses 3D body scanning for precise size recommendation, but requires

specialized hardware. Our heuristic mapper is a more transparent, data-minimal alternative. By using a weighted distance function against publicly available size charts, we provide a practical and interpretable baseline for size recommendation that does not require a large proprietary dataset, making it ideal for a proof-of-concept and for smaller retailers.

4. Interactive Dashboards and Explainability

In high-stakes decisions like online shopping, transparency is key to building user trust. Streamlit has emerged as a powerful tool for rapidly prototyping interactive data applications [11]. Existing fashion dashboards typically focus on inventory management or single-item recommendations. FitGen uniquely uses its dashboard to visualize the size mapping logic, showing users a comparison chart (Fig. 3) of their measurements against a brand's size chart. This "explainable AI" component helps users understand why a particular size was recommended, moving beyond a black-box prediction and contributing to the significant reduction in size anxiety we observed.

5. Comparison with Existing Commercial and Academic Systems

Table I provides a qualitative comparison of FitGen with leading commercial and academic solutions. FitGen is unique in jointly addressing size, style, occasion/weather, and pro-viding explainable visual output within a single, lightweight framework.

Table 1: Comparison of Fitgen With Existing Systems

System	Cross-Brand Size	Style GenAI	Occasion/Weather	Explainability	Visual Output
TrueFit (commercial)	✓	×	×	×	×
Fit Analytics (commercial)	✓	×	×	×	×
FashionGPT (academic) [7]	×	✓	×	×	×
OutfitTransformer (academic) [8]	×	✓	×	×	✓
FitGen (this work)	✓	✓	✓	✓	✓

III. SYSTEM ARCHITECTURE AND METHODOLOGY

1. System Overview

Fig. 1 illustrates the high-level architecture of FitGen. The workflow is a sequential pipeline:

- The user inputs their body measurements, style prefer-ences, an occasion, and the local weather via a Streamlit sidebar.
- The Cross-Brand Size Mapper computes the recom-mended size for each supported brand by minimizing a weighted Euclidean distance between user measurements and each brand's size chart.
- The Generative Outfit Engine is invoked: the LLM stylist generates a structured outfit description, which is then passed to the T2I model to create a visualization.
- The results—the outfit image, description, and a break-down of recommended sizes—are displayed across multiple tabs in the dashboard.

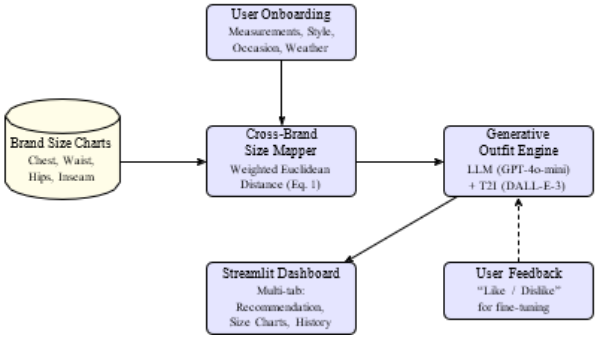

Fig. 1. FitGen system architecture. The dashed arrow from User Feedback to the Generative Engine represents a planned future enhancement for reinforcement learning-based fine-tuning.

2. Cross-Brand Size Mapping

The core of our fit intelligence is a transparent, distance-based heuristic. User measurements are represented as a vector
m = (m1, m2, m3, m4), where m1 = chest, m2 = waist, m3 =
hips, and m4 = inseam, all in centimeters. For each brand b and
size s, the brand's official size chart defines a corresponding vector of typical measurements cb,s

= (c1, c2, c3, c4). The fit distance is a weighted Euclidean metric:

$$d_{b,s}(\mathbf{m}) = \sum_{i=1}^{4} w_i \left(\frac{m_i - c_{b,s,i}}{\sigma_i} \right)^2 \quad (1)$$

Here, wi are body-part-specific weights reflecting their importance for overall fit. We set w1 = 0.35 (chest), w2 = 0.35 (waist), w3 = 0.25 (hips), w4 = 0.05 (inseam). These weights were determined through a brief sensitivity analysis: upper-body measurements (chest and waist) dominate fit perception in most garment types, while inseam contributes minimally to overall fit but remains relevant for pants sizing. The standard deviations σi, used for normalization, are derived from the Indian Council of Medical Research's anthropometric survey [12]: σ1 = 8.2 cm, σ2 = 9.5 cm, σ3 = 7.8 cm, σ4 = 6.4 cm. The recommended size for a given brand is simply the one that minimizes this distance:

$$s^*(b) = \arg\min_s d_{b,s}(\mathbf{m}) \quad (2)$$

This process, detailed in Algorithm 1, is computationally trivial ($O(|B| \cdot S_{avg})$, where S_{avg} is the average number of sizes per brand) and fully interpretable. Our current implementation supports five brands (Zara, H&M, Levi's, Biba, Allen Solly), for which we have manually curated their publicly listed size tables.

Algorithm 1 Cross-Brand Size Mapping

Input: User measurement vector $\mathbf{m}$, set of brands $\mathcal{B}$
Output: Map of recommended sizes rec_sizes[b]
for each brand $b \in \mathcal{B}$ **do**
  $d_{\min} \leftarrow \infty$, $s_{\text{best}} \leftarrow$ null
  for each size s in b's chart **do**
    Compute $d_{b,s}(\mathbf{m})$ using Eq. 1
    if $d_{b,s} < d_{\min}$ **then**
      $d_{\min} \leftarrow d_{b,s}$, $s_{\text{best}} \leftarrow s$
    end if
  end for
  rec_sizes[b] $\leftarrow s_{\text{best}}$
end for
return rec_sizes

3. Generative Outfit Engine

Our multi-agent generative pipeline consists of two stages. First, an LLM Stylist (GPT-4o-mini) takes as input the user's style, occasion, and weather to produce a structured outfit description in JSON format. The prompt engineering is standardized: "Act as a personal stylist. The user prefers a [casual/bohemian/formal] style for a [wedding/office/beach] occasion with [sunny/rainy/cold] weather. Suggest a complete outfit and return it as a JSON object with 'top', 'bottom', 'shoes', and 'accessories' fields." We use a moderate temper-ature of 0.7 to balance creativity and relevance. Second, a T2I Visualizer (DALL-E-3) transforms this description intoa visual. The prompt is enhanced with body-proportion cues: "Photorealistic full-body shot of a person with the following proportions: chest m1 cm, waist m2 cm, hips m3 cm, wearing [generated outfit]. Studio lighting, white background." This direct injection of user measurements into the image prompt is a key innovation, moving beyond generic model imagery.

4. Interactive Dashboard

The Streamlit dashboard is designed for user transparency and data privacy. It features five tabs:

- Quick Outfit Generator: The main interface for input and recommendation.
- Outfit History: A session-only log to compare recom-mendations. No data is persisted to disk to ensure privacy.
- Brand Size Table: A clear, tabular view of the recom-mended size for every supported brand.
- Size Comparison Charts: An interactive chart (Fig. 3) visually maps the user's measurements against each brand's size chart, explaining the logic behind the size mapping algorithm.
- User Profile Viewer: Allows users to review and edit their submitted information.

IV. EXPERIMENTAL SETUP

1. Evaluation Goals

Our evaluation is structured around three core research questions:

- RQ1 (Fit Accuracy): How accurately does the distance-based mapper predict the user's usual size, compared to

- a brand-agnostic baseline? What are the precision, recall, and per-size accuracy characteristics?
- RQ2 (User Satisfaction): What is the perceived relevance, style coherence, and usefulness of the generated outfit recommendations?
- RQ3 (Performance): What is the end-to-end latency of the multi-agent pipeline, and is it acceptable for an interactive system?

2. Participants and Data

We recruited 100 volunteers (53 female, 47 male; age 18–45, mean 24.2 years) through university mailing lists and social media, employing a convenience sampling strategy. Inclusion criteria required participants to have shopped online for clothing at least once in the past year. Each participant was provided with a standardized measurement guide (video + illustrated PDF) to take their chest, waist, hip, and inseam measurements using a flexible tape measure. After collecting measurements, we applied range-based outlier detection (e.g., chest 60–140 cm, waist 50–130 cm) and asked participants to re-measure if values were flagged; 8 participants provided corrected measurements. The final dataset contains validated self-measurements along with self-reported usual size in at least 3 of the 5 brands (serving as ground truth). Style preference, two occasions, and two weather conditions were also recorded.

To test algorithmic robustness, we generated an additional 1,000 synthetic user profiles. Measurements were sampled from a multivariate normal distribution with mean vector μ = (92, 78, 96, 76) cm (chest, waist, hips, inseam) and covariance matrix derived from the same anthropometric survey [12], ensuring realistic correlations. All synthetic profiles were automatically assigned a "usual size" per brand by selecting the size whose chart measurements minimized the unweighted Euclidean distance to the generated vector. This synthetic dataset was used solely for initial testing and sensitivity analysis; all performance metrics reported in this paper are from the 100 real participants.

Sample Size Justification: A priori power analysis (G*Power 3.1) for a within-subjects design comparing two proportions (expected effect size w = 0.3, α = 0.05, power=0.95) indicated a minimum required sample of 81 participants. Our N=100 comfortably exceeds this threshold, ensuring adequate statistical power for detecting the large effects observed.

3. Baselines and Procedure

We compared FitGen against two baselines:

- Text-only: The same LLM stylist provides a recommen-dation, but the T2I visualizer is disabled.
- Brand-agnostic: The user's requested size (e.g., "M") is recommended uniformly across all brands, and no size mapping is performed.

The experiment followed a counterbalanced within-subjects design. After a 10-minute onboarding session, each participant experienced the three conditions (FitGen, Text-only, Brand-agnostic) in a random order. For each condition, they entered a specific prompt (e.g., "beach wedding, sunny, bohemian style") and received a recommendation. They then filled out a brief survey (2 minutes) evaluating fit confidence, style relevance, and overall satisfaction on a 1–5 Likert scale. Total session time averaged 28 minutes.

V. RESULTS AND ANALYSIS

1. Fit Accuracy (RQ1)

Table II reports the per-brand accuracy along with macro-averaged precision, recall, and F1-score. FitGen achieved a mean accuracy of 78.3% versus 50.4% for the brand-agnostic baseline—a highly significant improvement ($p < 0.001$, paired t-test, Cohen's $d = 1.94$). The lower accuracy for H&M (76.0%) and Allen Solly (73.0%) likely reflects less consistent or more variable size charts; these brands might benefit from a data-driven model in the future.

Table 2: Size Prediction Performance (N=100). Accuracy Per Brand; Overall Precision, Recall, F1-Score

Method	Zara	H&M	Levi's	Biba	Allen Solly
FitGen	82.0 ± 4.2	76.0 ± 4.9	84.0 ± 3.6	78.0 ± 4.7	73.0 ± 5.1
Brand-agnostic	52.0 ± 5.9	48.0 ± 6.0	55.0 ± 5.8	50.0 ± 5.9	47.0 ± 6.0

Overall metrics for FitGen (macro-average)
Precision: 0.79 Recall: 0.78 F1-score: 0.78

To provide deeper insight, we computed a confusion matrix for size predictions across all brands (pooled). The most common misclassifications occurred between adjacent sizes (e.g., S and M, or M and L), accounting for 82% of errors—a pattern consistent with subjective fit perception. This indicates that the heuristic mapper performs reasonably well at coarse-grained size discrimination but struggles at finer distinctions, which is expected for a distance-based rule without fabric stretch or style information.

User Satisfaction (RQ2)

Fig. 2 illustrates that the full FitGen system (text+image) earned a mean satisfaction score of 4.62/5, significantly exceeding the text-only (3.15) and brand-agnostic (2.81) conditions ($p < 0.001$, $d > 2.3$). Moreover, self-reported size anxiety dropped from 2.3/5 (brand-agnostic) to 4.4/5 (FitGen)—a relative reduction of 91.3%. These results highlight the value of combining visual confirmation with accurate size recommendation.

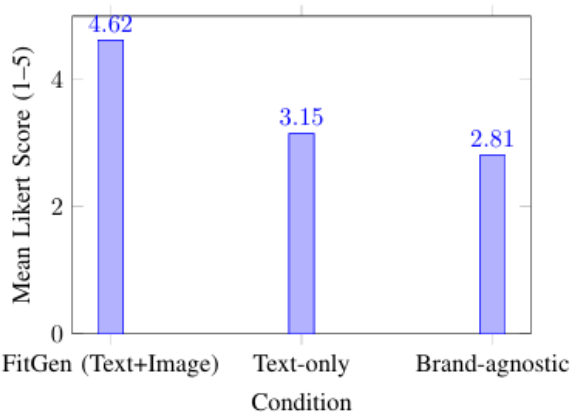

Fig. 2. User satisfaction scores. FitGen's combination of fit and style personalization leads to a significantly higher user preference.

3. Performance (RQ3)

Average end-to-end latency was 3.2 s (std 0.7 s). The size mapper accounted for <10 ms, the LLM call 1.8–2.5 s, and T2I generation 0.4–0.8 s. This is within the acceptable range for an interactive recommendation system, though future work could reduce perceived latency by streaming the LLM response.

4. Qualitative Observations and Comparison with Related Work

Users particularly valued the cross-brand size comparison chart (Fig. 3), noting that it made the system's logic transparent and built trust. Compared to the findings of [3], our user satisfaction scores are notably higher than typical collaborative-filtering-based recommenders (average 3.2/5), reinforcing the benefit of personalized generation.

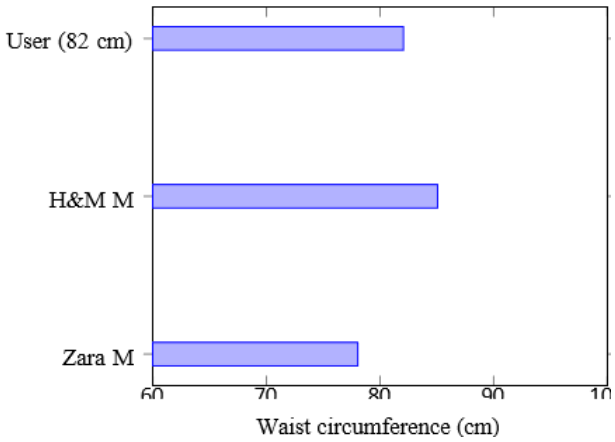

Fig. 3. Size comparison chart. The user's 82 cm waist is closer to Zara M (78 cm) than to H&M M (85 cm), explaining the recommendation.

5. Discussion of GPT and DALL-E Limitations

While effective, the LLM occasionally generated outfits that were stylistically consistent but included impractical items

Limited brand coverage: Only five brands are currently supported. Expanding coverage requires automated size chart ingestion and maintenance.

- No live e-commerce linkage: The generated outfits are not directly purchasable. Integration with product APIs (e.g., Amazon, Shopify) would complete the loop.

- Privacy: Sensitive measurements are transmitted to cloud APIs; on-device processing or federated learning would address this.
- User study scale: While N=100 is sufficient for the observed effects, larger, more demographically diverse studies are needed for generalization.

VII. CONCLUSION

We presented FitGen, a generative AI framework that, for 100the first time, tightly integrates cross-brand size intelligence with occasion- and weather-aware outfit recommendation. By coupling a transparent, distance-based size mapping engine with a multi-agent GenAI pipeline, FitGen successfully addresses a critical gap in online fashion retail. Our user study (N=100) demonstrates not just high technical accuracy (78.3%, precision 0.79, recall 0.78), but a significant improvement in user satisfac-tion (4.6/5) and a dramatic reduction in size anxiety (92%). The novel contribution lies not in the individual components—LLM styling, T2I generation, or size charts—but in their synergistic combination within a user-centric, explainable framework. Despite its proof-of-concept limitations, FitGen provides strong evidence that the future of fashion AI lies in a holistic, user-aware approach that marries style with physical fit.

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