

Solving The Universal Clothing Size Crisis Using AI-Driven Fit Systems And 3D Visualization: A Design Thinking Approach

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Abstract

Purpose: This study addresses the global clothing size inconsistency problem and evaluates AI-driven fit systems and 3D visualization technologies to improve fit accuracy and reduce return rates in online fashion retail.

Design/Methodology/Approach: A quantitative survey design was employed with $n=50$ respondents using 5-point Likert scales. Internal consistency was verified via Cronbach's alpha. Ordinary least squares (OLS) regression was used to examine relationships between fit-tech usage, consumer engagement, and purchase outcomes.

Findings: Fit-tech usage significantly improves customer confidence and engagement ($R^2=0.69$, $p<0.05$), while its direct effect on purchase outcomes is weaker and statistically non-significant ($R^2=0.016$, $p>0.05$).

Practical Implications: Adoption of AI sizing and 3D visualization tools can meaningfully reduce return rates and improve satisfaction, but retailers must address additional barriers to convert engagement into purchase decisions.

Originality/Value: This study provides empirical evidence on fit-tech adoption using primary survey data in the Indian consumer context, an area underexplored in existing literature.

Keywords: Clothing Size Crisis; AI-Driven Sizing; 3D Virtual Try-On; Fashion Technology; E-commerce Returns; Consumer Behavior; Regression Analysis

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I. Introduction

The fashion industry faces a persistent and costly problem: global size inconsistency across brands and regions. With the rapid growth of e-commerce, consumers increasingly purchase apparel online without the ability to physically try garments, leading to widespread fit uncertainty. Studies suggest that 30–40% of all online apparel purchases are returned, with poor fit identified as the leading cause (Apeageyi, 2008; Chun, 2020). This generates enormous financial and environmental costs for retailers, logistics providers, and consumers alike.

Emerging technologies such as AI-driven sizing algorithms and 3D virtual try-on (VTO) systems offer promising solutions. These tools use consumer body data—height, weight, body shape, and purchase history—to generate personalized size recommendations and enable digital garment visualization before purchase. However, empirical evidence on how these tools affect consumer engagement and actual purchase decisions remains limited, particularly in emerging market contexts.

This study applies a Design Thinking framework to investigate: (1) how fit-tech usage impacts consumer engagement, and (2) whether improved engagement translates into better purchase outcomes. Using a quantitative survey approach with Indian consumers, this paper contributes to the growing body of literature on fashion technology adoption and e-commerce return management.

II. Literature Review

Size Inconsistency and E-commerce Returns

Inconsistent sizing across brands is one of the most documented challenges in fashion retail. Apeageyi (2008) identified body measurement discrepancies as a fundamental driver of consumer dissatisfaction in apparel purchases. More recently, Chun (2020) confirmed that sizing uncertainty is the primary reason for return initiation in online fashion, accounting for approximately 38% of all returns in major e-commerce markets. The environmental costs of return logistics are also significant, with McKinsey & Company (2020) estimating that returns contribute substantially to fashion's carbon footprint.

AI-Driven Sizing Solutions

Machine learning models for size recommendation have gained academic and commercial attention. Heuritech (2021) demonstrated that AI algorithms using customer anthropometric data can improve size recommendation accuracy by up to 25%, reducing return rates correspondingly. Ashdown and Dunne (2006) emphasized the importance of 3D body scanning data for developing better sizing systems, while Park and Stool (2005) showed that perceived fit risk significantly mediates online purchase intention. More recent research (Bertram et al., 2023) confirms that AI-based personalization reduces perceived risk during online shopping.

3D Visualization and Virtual Try-On

Three-dimensional body scanning and virtual try-on technologies enable consumers to visualize garment fit digitally. Fiore et al. (2005) found that 3D product visualization enhances consumer enjoyment and purchase confidence. Kim and Forsythe (2008) further demonstrated that virtual try-on technology reduces perceived risk and improves purchase intention, particularly for high-involvement fashion items. However, adoption barriers—including cost, technical complexity, and consumer trust—remain significant (Pantano & Pizzi, 2020).

The Engagement-Purchase Gap

Several studies note a discrepancy between technology-driven engagement and actual purchase conversion. Verhagen and van Dolen (2011) found that while interactive digital tools improve browsing engagement, their effect on final purchase decisions is moderated by factors such as price sensitivity, brand loyalty, and user experience design. This suggests that fit-tech tools may increase consumer interest and confidence without necessarily converting that interest into immediate purchases—a gap this study seeks to empirically examine.

III. Methodology

Research Design

This study adopts a quantitative, cross-sectional survey design. Primary data was collected from 50 respondents using a structured questionnaire with 5-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree). The survey measured three constructs: Fit-Tech Usage (X), Consumer Engagement (Y1), and Purchase Outcome (Y2). The Design Thinking framework was applied to frame the problem, empathize with end users, and evaluate technology-driven solutions.

Sampling

A convenience sampling method was employed targeting online apparel shoppers familiar with or exposed to fit-tech tools. The sample consisted of 50 respondents, which, while modest, is sufficient for exploratory regression analysis. Respondents were drawn from urban Indian consumers aged 18–35 with prior e-commerce fashion purchase experience.

Data Analysis

Data was analyzed using Microsoft Excel for descriptive statistics (mean, standard deviation, range) and Ordinary Least Squares (OLS) regression analysis. Internal consistency of the Likert scale items was assessed using Cronbach's alpha coefficient. Two separate regression models were estimated: (1) Fit-Tech Usage → Consumer Engagement, and (2) Fit-Tech Usage → Purchase Outcome.

IV. Hypothesis Development

H1₀: Fit-tech usage has no significant impact on consumer engagement.

H1_A: Fit-tech usage has a significant positive impact on consumer engagement.

H2₀: Fit-tech usage has no significant impact on purchase outcomes.

H2_A: Fit-tech usage has a significant positive impact on purchase outcomes.

V. Data Analysis And Findings

Reliability Testing

Cronbach's Alpha (α) = 0.96 ($\alpha > 0.7$ confirms acceptable internal consistency; $\alpha > 0.9$ indicates excellent reliability; Hair et al., 2019).

Descriptive Statistics

Table 1: Descriptive Statistics of Study Variables

| Variable | Mean | Std. Dev. | Range |
|--------------------------|------|-----------|-----------|
| Fit-Tech Usage (X) | 2.74 | 1.51 | 1.0 – 5.0 |
| Consumer Engagement (Y1) | 2.92 | 1.12 | 1.0 – 5.0 |
| Purchase Outcome (Y2) | 2.60 | 0.98 | 1.0 – 4.6 |

Note: All variables measured on 5-point Likert scales (1=Strongly Disagree; 5=Strongly Agree).

Regression Analysis — Model 1: Fit-Tech Usage vs. Consumer Engagement

Table 2: Regression Results — Fit-Tech Usage → Consumer Engagement

| Metric | Value | Interpretation |
|----------------------------|--------|-----------------------------|
| Multiple R | 0.8336 | Strong positive correlation |
| R Square (R ²) | 0.6949 | 69.5% variance explained |
| Adjusted R ² | 0.6819 | Model fit confirmed |
| Standard Error | 0.6299 | — |
| Observations | 50 | — |
| F-statistic | 109.33 | p < 0.05 (Significant) |

Decision: p < 0.05 → Reject H1₀; Accept H1A. Fit-tech usage significantly predicts consumer engagement.

Interpretation: Fit-tech usage explains approximately 69.5% of the variance in consumer engagement (R²=0.69), a strong effect (Cohen, 1988). This supports the hypothesis that AI-driven sizing and 3D visualization tools meaningfully enhance consumer engagement during online fashion shopping.

Regression Analysis — Model 2: Fit-Tech Usage vs. Purchase Outcome

Table 3: Regression Results — Fit-Tech Usage → Purchase Outcome

| Metric | Value | Interpretation |
|----------------------------|---------|----------------------------|
| Multiple R | 0.1285 | Weak correlation |
| R Square (R ²) | 0.0165 | 1.6% variance explained |
| Adjusted R ² | -0.0253 | Model not significant |
| Standard Error | 0.9941 | — |
| Observations | 50 | — |
| F-statistic | 0.806 | p > 0.05 (Not Significant) |

Decision: p > 0.05 → Fail to Reject H2₀. Fit-tech usage does not significantly predict purchase outcomes.

Interpretation: Fit-tech usage explains only 1.6% of variance in purchase outcomes (R²=0.016), a negligible and statistically non-significant effect. This finding is consistent with Verhagen and van Dolen (2011), who identified moderating variables—such as price sensitivity, brand loyalty, and UX design—that intervene between engagement and purchase conversion.

Hypothesis Testing Summary

Table 4: Hypothesis Testing Summary

| Hypothesis | Statement | Result |
|-----------------|--|-----------------------|
| H1 ₀ | Fit-tech has no impact on engagement | Rejected (p<0.05) |
| H1A | Fit-tech positively impacts engagement | Supported ✓ |
| H2 ₀ | Fit-tech has no impact on purchase outcome | Not Rejected (p>0.05) |
| H2A | Fit-tech positively impacts purchase outcome | Not Supported X |

VI. Discussion

The findings reveal an important distinction in how fit-tech tools influence consumer behavior. The strong and significant relationship between fit-tech usage and engagement ($R^2=0.69$) confirms that AI sizing and 3D visualization meaningfully improve customer confidence, reduce perceived fit risk, and increase interaction with product listings. This aligns with Kim and Forsythe (2008) and Fiore et al. (2005), who documented positive effects of virtual try-on on engagement and purchase confidence.

However, the non-significant relationship between fit-tech usage and purchase outcomes ($R^2=0.016$) suggests that engagement does not automatically translate into purchase conversion. This gap is consistent with literature on the 'engagement-purchase paradox' in e-commerce, where consumers may extensively interact with digital tools yet delay or abandon purchase due to external factors. For fashion retail specifically, price perception, brand trust, delivery timelines, and overall UX design likely moderate the fit-tech → purchase pathway.

These findings have important strategic implications: retailers should not evaluate fit-tech ROI solely on immediate sales conversion. Instead, engagement metrics—time-on-site, product exploration depth, wishlist additions—may be more appropriate short-term indicators of fit-tech effectiveness, with purchase conversion emerging as a longer-term outcome.

VII. Limitations And Future Research

This study has several limitations that should be acknowledged. First, the sample size of $n=50$ is modest, which limits statistical power and generalizability. Future studies should target larger, more geographically diverse samples. Second, convenience sampling may introduce selection bias, as respondents may disproportionately represent tech-savvy consumers. Third, the cross-sectional design cannot establish causality; longitudinal studies tracking actual purchase behavior over time would provide stronger evidence.

Future research directions include: (1) examining mediating variables (brand loyalty, price sensitivity) in the fit-tech → purchase relationship; (2) comparing fit-tech effectiveness across different product categories (formal wear vs. casual wear); (3) investigating differences in adoption between urban and rural Indian consumers; and (4) testing whether specific types of fit-tech (AI sizing vs. 3D VTO) differ in their impact on engagement and conversion.

VIII. Conclusion

This study provides empirical evidence that AI-driven fit systems and 3D visualization technologies significantly improve consumer engagement in online fashion retail ($R^2=0.69$, $p<0.05$), supporting H1A. However, the direct impact on purchase outcomes was not statistically significant ($R^2=0.016$, $p>0.05$), suggesting that other factors mediate the engagement-to-purchase conversion process.

From a managerial perspective, fashion retailers should invest in fit-tech as a long-term engagement and trust-building tool rather than expecting immediate purchase conversion. Combining AI sizing tools with complementary strategies—transparent return policies, competitive pricing, and seamless UX—is likely to maximize the commercial impact of these technologies. As fit-tech adoption scales, it has the potential to substantially reduce return rates, improve customer satisfaction, and lower the environmental costs of fashion logistics.

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