CCS4340-Machine Learning

# CEYLON CRUSH

## MARKET RESEARCH

TEAM STYLEMIND


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# 1. Introduction

## 1.1. Project Overview

Several changes have swept through the world of e-commerce business, and especially in the fashion trade with the constant development of artificial intelligence (AI) and machine learning (ML) sphere. Customers are eager to obtain individual, interactive and seamless shopping experiences, whereas fashion retailers aim at minimizing returns of items, enhancing the correctness of their recommendation systems, and predicting fashion trends. This project, which is referred to as AI-Driven Market Research, Innovation Proposal, and Product Reengineering of CeylonCrush-An Intelligent Fashion-Tech Platform was undertaken with the prospect of discussing how the current ML methods can be applied as the means of revolutionizing the Sri Lankan homegrown fashion/e-commerce company CeylonCrush to a globally involved, intelligent, and competitive platform.

The project represents a complex approach that incorporates field market study, competitor study, user experience exploration, and an in-depth study of the possibility of integration of modern machine learning capabilities. As a ten-member interdisciplinary team, we had to jump in and create some innovation in the online shopping experience by evaluating viability and AI-based technical design thought.

## 1.2. Objective of the Project

The main purpose of this group assignment will be an assessment of the ability of students to implement ML methodology to address challenges of the industry level. In particular, the project is expected:

- Undertake thorough consumer and influencer market research to identify the main pain points of online fashion retail.
- Find omissions in local and global competitors' platforms.
- Coming up with and establishing new ML fragmentations which enhance user participation, contentment, and efficiency.
- Revisit the current product frameworks on microservices, AI models, and scalable architecture.

Come up with a business and deployment plan that not only makes it commercially viable but also technically sustainable.

The parameters around which this objective is followed are with reference of a practical approach, standard tools of the industry, the framework that allows them to grow over a long period of time, security, and modules.

## 2. Market Research & Survey Analysis

### 2.1. Introduction & Survey Methodology

CeylonCrush is a next-gen fashion e-commerce platform built in Sri Lanka, leveraging AI and ML models to provide smart fashion solutions. It aims to revolutionize the online shopping experience by offering virtual try-on capabilities, personalized fashion recommendations, influencer shop integration, and promoting local fashion brands. The platform's mission is to bridge the gap between fashion and technology while catering to young, trend-conscious Sri Lankan consumers.

The purpose of this research is to understand the behavior, preferences, and challenges of online fashion shoppers in Sri Lanka. It focuses on user acceptance of AI-driven personalization, interest in virtual try-on, and the influence of social media and influencers on purchase decisions. These insights are crucial for shaping CeylonCrush's features and improving user experience.

The data was collected via a Google Forms survey shared with over 100 Sri Lankans. The survey contained 19 questions, including multiple-choice, Likert-scale, and open-ended formats. The responses were exported to CSV and analyzed to uncover trends and preferences in the online fashion space.

**Methodology**

- **Data Collection**: Google Forms
- **Sample Size**: 113 participants
- **Question Format**: Multiple-choice, Likert scales, and open-ended responses.

  Survey csv link - https://docs.google.com/spreadsheets/d/11DYDdKzybTzf6UqIWgJATFGk_LLGnIMVDXqkpQoUFno/edit?usp=drive_link

### 2.2. Respondent Demographics

### 2.2.1. Age Distribution

- 25–34 years – 56 respondents (50%)
- 18–24 years – 46 respondents (41%)
- Under 18 – 6 respondents
- 45–54 years – 5 respondents

**Analysis:** Young adults are the primary users, aligning with global fashion tech trends.

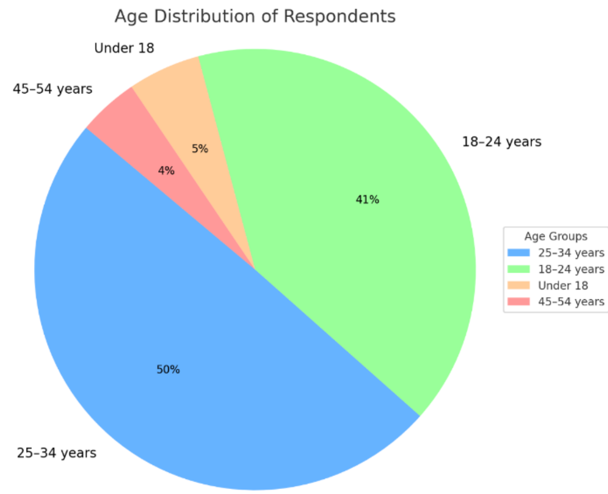



*Figure 2.1*

A majority of participants were between the ages of 18 and 34, with 50% falling in the 25–34 category and 41% in the 18–24 range. This confirms that the survey captured the target audience of tech-savvy young adults, who are also the most active demographic in online fashion shopping globally. Smaller representations from under-18 and 45–54 age groups show potential for broader market outreach.

## 2.2.2. Gender

- Female – 71 respondents (63%)
- Male – 42 respondents (37%)

**Analysis:**

The female-majority response (63%) highlights a key target audience, as women are typically more engaged with fashion shopping and influencer content.

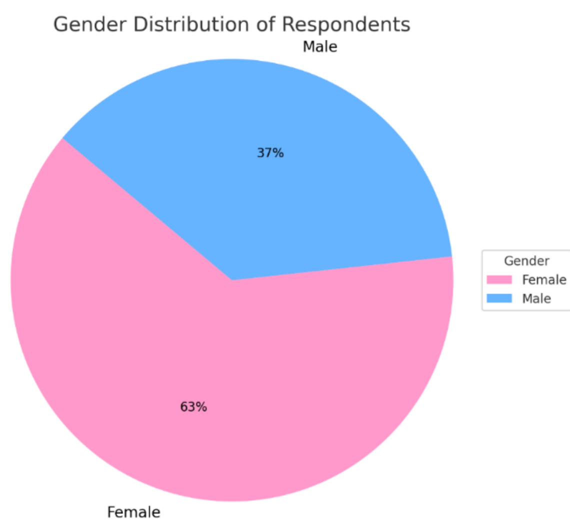



*Figure 2.2*

Out of 113 respondents, **71 identified as female** (63%) and **42 as male**. The female-majority result is significant, as women tend to be more engaged in fashion shopping and influencer content. This supports the brand's focus on visual engagement, style-based features, and community building within its platform.

### 2.2.3. Location

**Top districts:**

- ❖ Colombo (24)
- ❖ Kalutara (24)
- ❖ Matara (14)
- ❖ Galle (13)
- ❖ Gampaha (10)

**Analysis-**Coastal and Western districts dominate the user base.

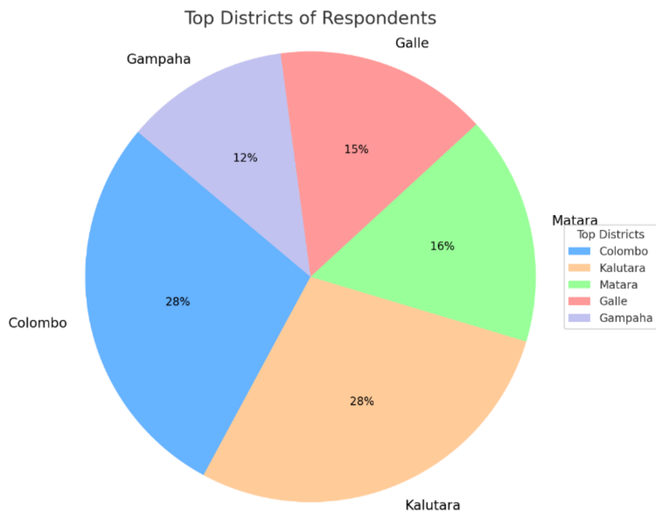



*Figure 2.3.*

Respondents were spread across 13+ districts, with the majority coming from **Colombo, Kalutara, Matara, Galle**, and **Gampaha**. These are highly urbanized and semi-urban regions with strong internet access, making them prime zones for fashion tech adoption. Colombo and Kalutara topped the chart, suggesting a strong early-adopter presence.

### 2.2.4. Occupation

- ❖ Students – 72
- ❖ Employed – 31

❖ Others (Self-employed, unemployed, businessmen) – 10

**Analysis-**Students are your biggest user group, suggesting high mobile/internet usage and trend-following behavior.

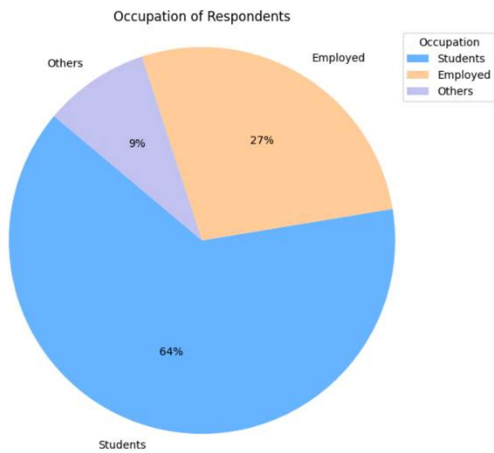



*Figure 2.4.*

More than 60% of participants were **students**, followed by employed individuals (27%). This again aligns with the brand's target audience: young, fashionable, internet-active individuals. A smaller percentage of unemployed, self-employed, and businesspeople also shared insights, indicating broader interest across economic backgrounds.

## 2.2.5. Fashion influencers on social media

❖ Yes → 81 (72%)

❖ No → 16 (14%)

❖ Maybe → 16(14%)

**Analysis-** Strong influencer-driven interest and major opportunity for influencer shop integration.

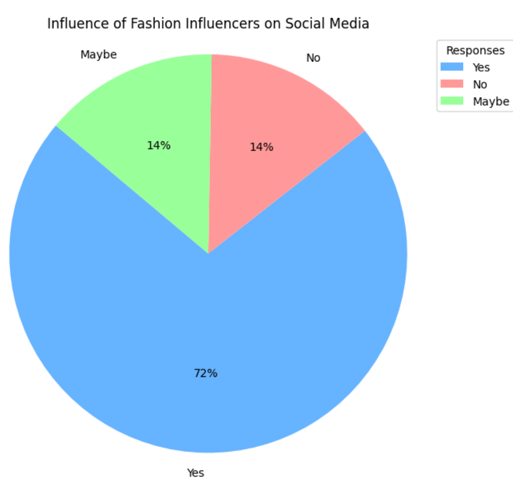



*Figure 2.5.*

A significant majority (72%) answered Yes, indicating a strong influence from social media in shaping fashion preferences. Meanwhile, 14% each selected No and Maybe, showing a smaller but notable segment that is either undecided or not influenced by online fashion figures. This highlights the importance of influencer marketing in fashion-related digital strategies.

## 2.3. Online Fashion Behavior & Influencer Impact

### 2.3.1 Online Shopping Frequency

- Occasionally – 46
- Rarely – 33
- Frequently – 23
- Always – 8
- Never – 3

**Analysis-** This suggests that online shopping is used on a need-based or selective basis rather than a habitual behavior for most people.

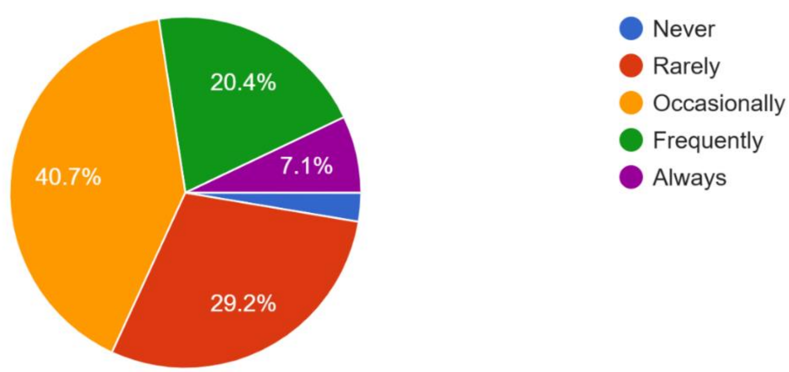



*Figure 2.6.*

The survey revealed that **41% of users shop online occasionally**, while **20% shop frequently,** and **7% always do**. This shows a regular engagement with online fashion platforms. However, 29% rarely or never shop online, indicating untapped segments that could be reached with the right trust-building features, such as AI recommendations and try-ons.

### 2.3.2. Platforms Used

**Most frequently mentioned:**

- Daraz- 50 (44.2%)
- Temu- 30 (26.5%)
- Instagram Shops- 53 (46.9%)
- Shein- 30 (26.5%)

- ❖ Amazon- 25 (22.1%)

**Analysis-**Strong mix of global + local platforms, indicating demand for competitive pricing and style.

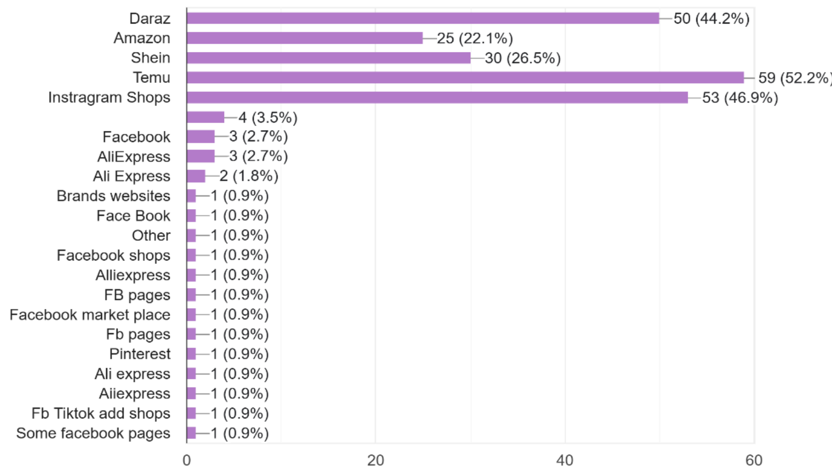



*Figure 2.7.*

When asked about platforms, respondents mentioned **Daraz, Temu, Instagram Shops, Shein, and Amazon** most often. The mix of global and local names suggests that shoppers prioritize **price, trend variety, and accessibility**. This also signals a competitive landscape and the need for CeylonCrush to differentiate through local brand visibility and superior tech features.

## 2.3.3. Factors Influencing the Purchase of Fashion Items Online

- ❖ Style/Trends -85 (75.2%)
- ❖ Price -72 (63.7%)
- ❖ Brand reputation -55 (48.7%)
- ❖ Recommendations -40 (35.4%)
- ❖ Visual presentation/images -37 (32.7%)
- ❖ Influencer reviews -34 (30.1%)
- ❖ Easy returns -26 (23%)
- ❖ Virtual try-on -10 (8.8%)
- ❖ Other -4 (3.6%)

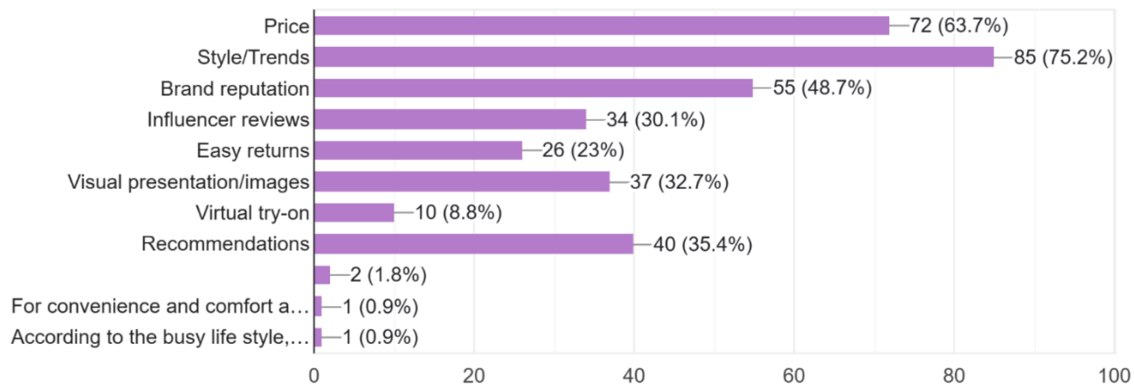



*Figure 2.8.*

The top factors influencing online fashion purchases are **Style/Trends (75.2%)** and **Price (63.7%)**, highlighting buyers' preference for fashionable and affordable items. **Brand reputation (48.7%)** and **Recommendations (35.4%)** also play a significant role. Visual appeal, influencer reviews, and return policies have a moderate impact, while **Virtual try-on (8.8%)** is the least influential. Overall, fashion sense and cost matter most to online shoppers.

## 2.4. Pain Points in Online Fashion Shopping

## 2.4.1. Common Challenges

- Size fitting issues – 81.4%
- Low confidence in product quality – 55.8%
- Inaccurate product images – 45.1%
- Hard to visualize outfits on oneself – 45.1%
- Return difficulties – 26.5%
- Lack of personalized suggestions – 17.7%
- Other – 0.9%

**Analysis-** The biggest friction areas are sizing and visual confidence.

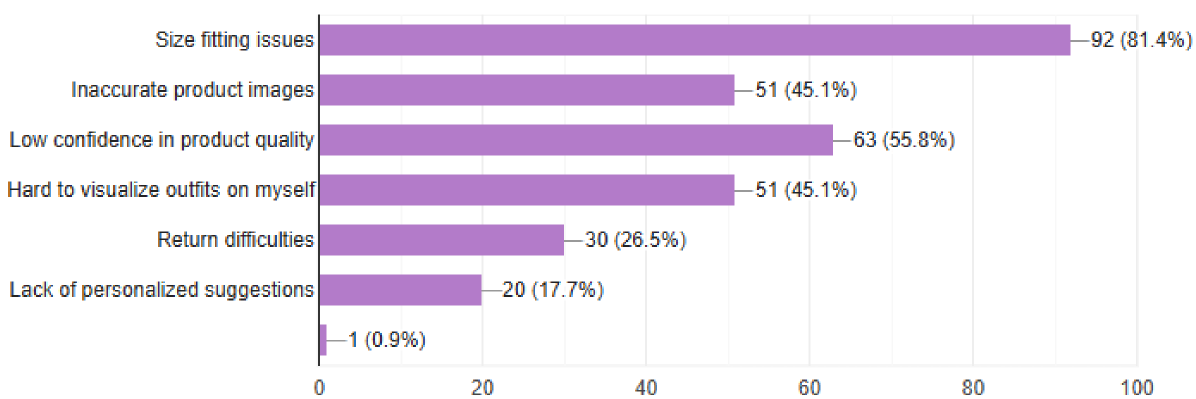



*Figure 2.9.*

Respondents cited **size fitting issues** as the most common challenge, followed by **inaccurate product images**, **low confidence in product quality**, **difficulty visualizing clothes on themselves**, and **return complications**. These issues are deeply connected to customer satisfaction and retention. Solving them can significantly enhance user loyalty.

### 2.4.2. Product Returns

- Yes- 62.8%
- No-37.2%

**Analysis-** 42 respondents (37%) have returned items because they didn't look good in person.

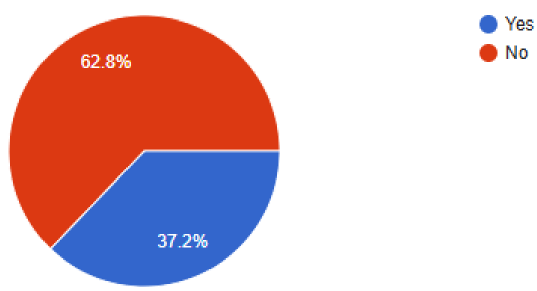



*Figure 2.10.*

When asked if they had ever returned an item because it didn't look good in person, **42 respondents (37%) said yes**. This underscores the importance of a feature like **virtual try-on**, which helps bridge the gap between product expectation and reality. Open-ended feedback revealed a strong desire for **accurate size guides**, **reliable product visuals**, **easy returns**, and **virtual try-on tools**.

## 2.5. Virtual Try-On & AI Personalization

### 2.5.1 Virtual Try-On Interest

- Definitely – 24(21.2%)
- Probably – 30(26.5%)
- Not sure – 29(25.7%)
- Probably not – 16(14.2%)
- Never – 14(12.4%)

**Analysis-**48% are open or enthusiastic; only 12% show resistance.

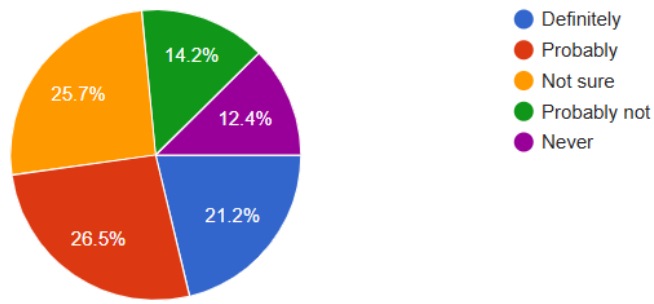



*Figure 2.11.*

More than **48% of users said they would definitely or probably use a virtual try-on feature**, while only **12% showed resistance**. This high interest indicates a strong market opportunity, especially if the feature is implemented in a user-friendly, privacy-conscious way.

## 2.5.2. Preferred Try-On Types

- ❖ Use a 3D avatar – 32
- ❖ Upload a photo – 26
- ❖ Use webcam/AR–19
- ❖ Not interested – 36

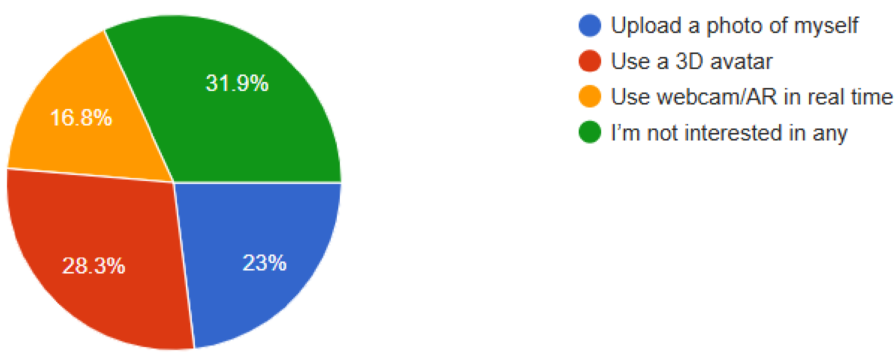



*Figure 2.12.*

Participants were divided on how they'd like to use virtual try-on:

- **28% prefer 3D avatars**
- **23% would upload a photo**
- **17% want AR via webcam**
- **32% are not currently interested**

Offering multiple methods can ensure inclusivity and reduce friction in adoption.

## 2.6. Confidence in AI Style Recommendations

## 2.6.1 Comfort Level with AI-Based Styling

| Score | Count | Percentage |
|---|---|---|
| 1 | 10 | 8.8% |
| 2 | 10 | 8.8% |
| 3 | 42 | 37.2% |
| 4 | 33 | 29.2% |
| 5 | 18 | 15.9% |

*Figure 2.13.*

**Analysis-** Majority of respondents (66%) rated 3 or 4, showing mild to moderate comfort with AI styling. This is a green light to begin integrating AI-driven suggestions, but with transparency and optional controls.

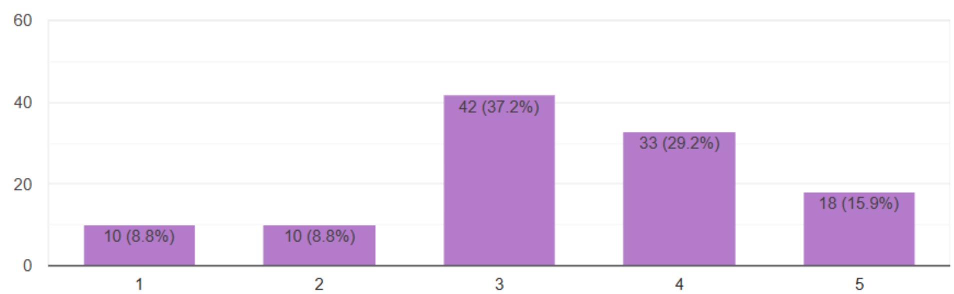



*Figure 2.14.*

Participants were asked to rate their **comfort with receiving fashion suggestions from an AI system** on a scale of 1 to 5. The results show that the **average comfort level is 3.35**. Most respondents selected mid-range values (3 and 4), which indicates a cautiously open attitude toward AI. Only a small group rated their comfort level below 2, reflecting a minority who are skeptical of automated recommendations.

## 2.6.2. Willingness to Try AI Recommendations

| Score | Count | Percentage |
|---|---|---|
| 1 | 9 | 8% |
| 2 | 11 | 9.7% |
| 3 | 38 | 33.6% |
| 4 | 40 | 35.4% |

| | | |
|---|---|---|
| 5 | 15 | 13.3% |

*Figure 2.15.*

**Analysis-**There is good potential for AI personalization, especially if recommendations reflect users' real tastes, body types, and local styles. Adding explainability.

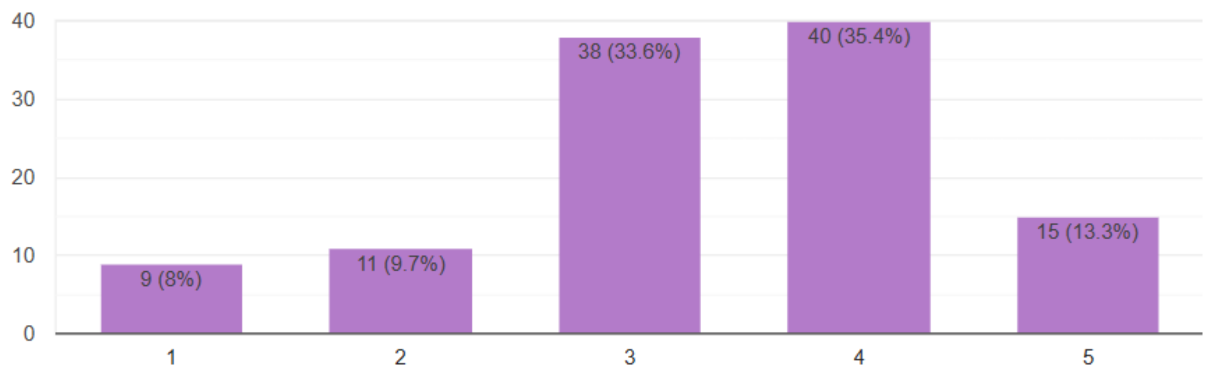



*Figure 2.16.*

When asked how likely they would be to try outfit recommendations generated by an AI system, respondents gave an average score of 3.36 out of 5. Once again, most answers clustered between 3 and 4, showing that users are willing to experiment but want personalization and relevance in return.

## 2.7. Influencer-Led Shopping Preferences

### 2.7.1. Following Fashion Influencers

| Answer | Count | Percent |
|---|---|---|
| Yes | 46 | 40.7% |
| No | 43 | 38.1% |
| Maybe | 24 | 21.2% |

*Figure 2.17.*

**Analysis**- 79% are at least somewhat influenced by online personalities, which shows how influencer impact translates into real shopping behavior.

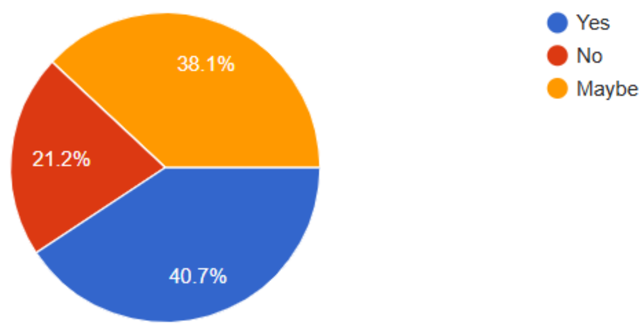



*Figure 2.18.*

Respondents were asked whether they had ever purchased an item based on an influencer's recommendation or look. Results show:

- **46 people said Yes**
- **43 said Maybe**
- **Only 24 said No**

This means **nearly 79% of respondents** are either influenced or potentially influenced by online personalities when it comes to purchasing fashion items.

## 2.7.2. Interest in Influencer Shop Integration

| Answer | Count | Percent |
|---|---|---|
| Yes, interested | 33 | 29.2% |
| Maybe | 61 | 54% |
| Not interested | 19 | 16.8% |

*Figure 2.19.*

**Analysis-** Over 83% of users are open to influencer-driven shopping features.

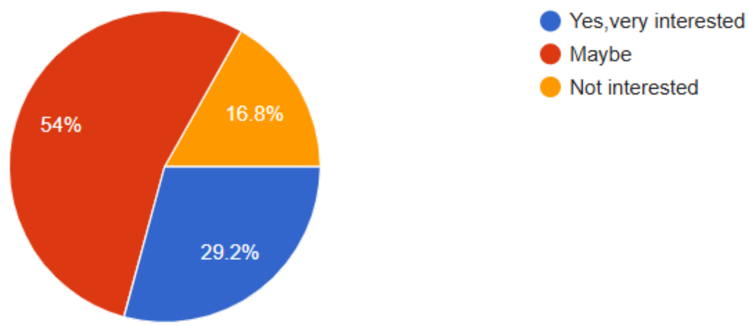



*Figure 2.20.*

When asked if they would use a feature that lets them see influencer outfits and directly purchase those items, here's how they responded:

- 33 people (29.2%) said Yes, very interested
- 61 people (54%) said Maybe
- 19 people (16.8%) said Not interested

Over 83% of users are either highly or potentially interested in an influencer-powered shopping experience**.**

## 2.8. User-Desired Features for an Improved Fashion Shopping Experience

- Customer Reviews and Ratings
- Accurate Size Charts
- Fabric Quality Information
- AI-Powered Recommendations
- Smart Filtering and Search
- 360° Product View & Zoom
- Exclusive Offers and Promotions
- Overall Shopping Convenience

When asked what would make their online fashion shopping experience better, many users shared practical and thoughtful suggestions. A common request was for customer reviews with real photos, as this helps build trust and gives a clearer idea of what to expect. Several mentioned the need for a proper size chart and more transparency about fabric quality, which would make choosing the right product much easier. People also wanted smarter ways to browse, like better filtering and search tools, so they can quickly find what they're looking for. Some respondents showed interest in AI-based recommendations that match their personal style, while others felt that being able to view products from all angles with a 360° view and zoom would help with decision-making. Offers and discounts were another popular suggestion, and overall, many simply wished for a more convenient and smooth shopping experience from start to finish.

## 3. Competitor Feature Benchmarking

## 3.1 Introduction

### 3.1.1 Purpose

Benchmark CeylonCrush against key competitors in Sri Lanka's fashion e-commerce market to identify gaps and opportunities.

### 3.1.2 Methodology

- **Data Sources:**
  - Chosen based on Survey responses (113 participants, Survey Database file).
  - Direct testing of competitor platforms (Daraz, Instagram Shops, Shein, Temu, Amazon).
- **Focus Areas:**
  - Virtual try-on, AI personalization, influencer integration, localization, Mobile responsiveness, Customer personalization, Payment, and language support

## 3.2 Competitor Selection

### 3.2.1 Top Platforms in Sri Lanka

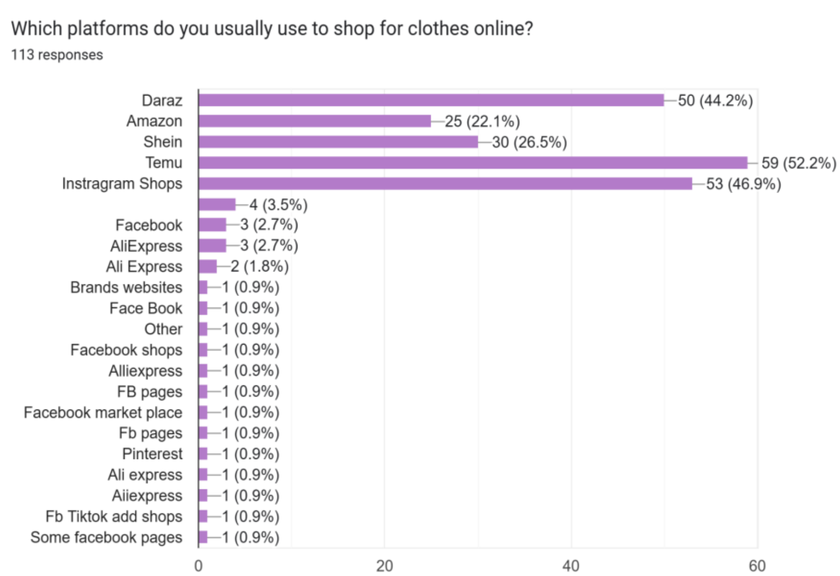



*Figure 3.1.*

**Competitor Overview**

| Platform | Strengths | Weaknesses | User Base |
|---|---|---|---|
| Daraz | Localized payments, COD | Poor product discovery | 44.2% |
| Amazon Fashion | Advanced AI recommendations | No Sinhala/Tamil support | 22.1% |
| Shein | Trend prediction | Difficulty in returns | 26.5% |
| Instagram Shops | Influencer integration | No size guides | 46.9% |
| Temu | low pricing | Quality concerns | 26.5% |

*Figure 3.2*

### 3.2.2 Selection Justification

- **Instagram Shops:** Leader in influencer-driven sales (survey Question 17: 83% interest).
- **Shein:** Best-in-class AI (survey Question 14: 66% comfort with AI styling).
- **Daraz:** Local leader but lacks try-on features (survey Question 10: 48% demand).

## 3.3 Feature Matrix

### 3.3.1 Scoring Criteria (1–5 Scale)

| Score | Definition |
|---|---|
| 5 | Industry-leading |
| 4 | Strong implementation |
| 3 | Basic functionality |
| 2 | Partial/poor execution |
| 1 | Lacks feature |

*Figure 3.3*

### 3.3.2 Feature Comparison

| Feature \ Platform | Daraz | Instagram Shops | Temu | Shein | Amazon |
|---|---|---|---|---|---|
| Virtual Try-On | 2 | 1 | 1 | 4 | 3 |
| AI Recommendations | 3 | 2 | 1 | 5 | 4 |
| Influencer Shops | 1 | 5 | 1 | 3 | 2 |
| Mobile Responsiveness | 4 | 5 | 3 | 4 | 4 |
| Customer Personalization | 3 | 2 | 2 | 5 | 4 |
| Sinhala Support | 4 | 3 | 2 | 2 | 1 |
| Easy Returns | 3 | 2 | 2 | 4 | 5 |

*Figure 3.4*

## 3.4 Comparative Analysis

### 3.4.1 Bar Chart: Feature Scores

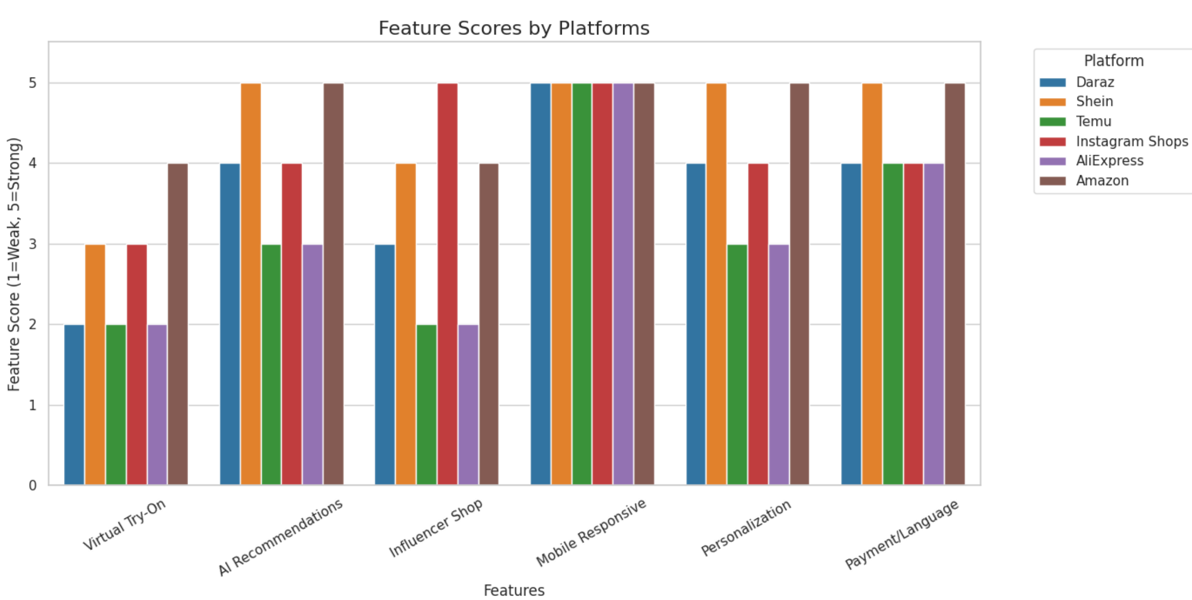



*Figure 3.5*

### 3.4.2 Heatmap: Strength vs. Weaknesses

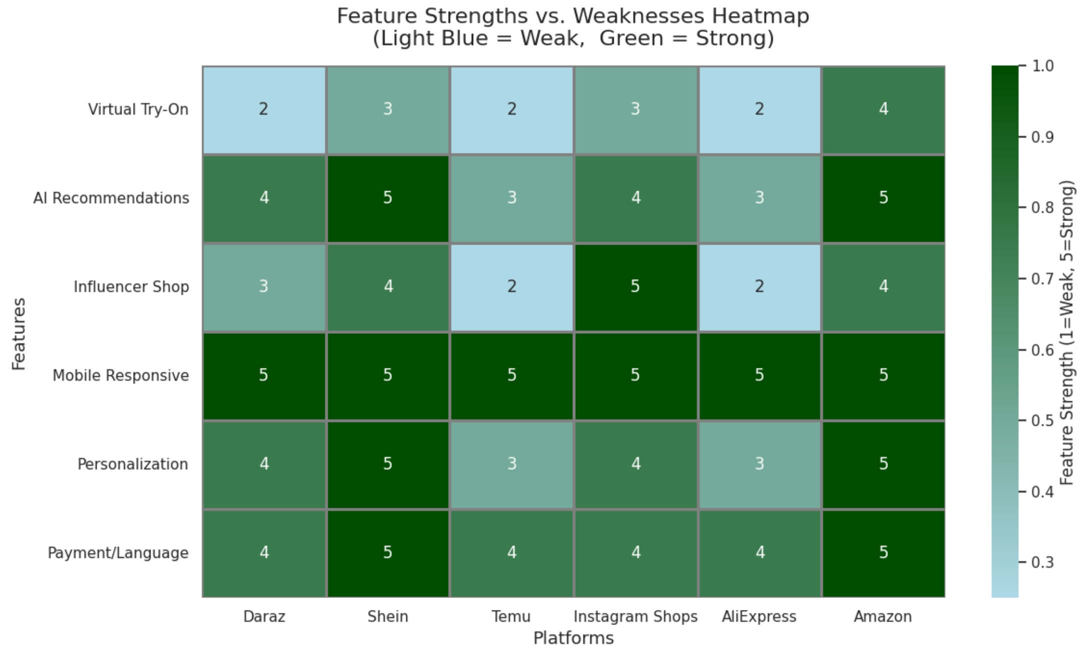



*Figure 3.6*

## 3.5 Key Observations

### 3.5.1 Gaps Identified

1. **Virtual Try-On:** Absent in all local platforms (Daraz/Temu), has 72% survey demand. Only Shein offers some related features.

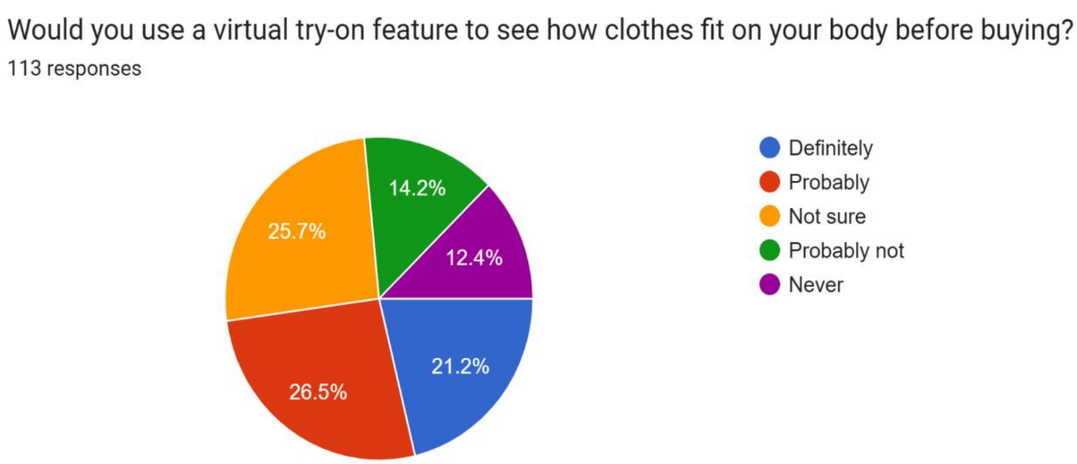



*Figure 3.7*

2. **Localization:** Only Daraz supports Sinhala (rated 3/5 for accuracy).
3. **AI Personalization:**
   - Shein (5/5) uses ML for recommendations.
   - *Survey Insight:* 35% want AI suggestions.

If the AI gave you outfit recommendations based on your previous purchases or preferences, how likely would you be to try them?
113 responses

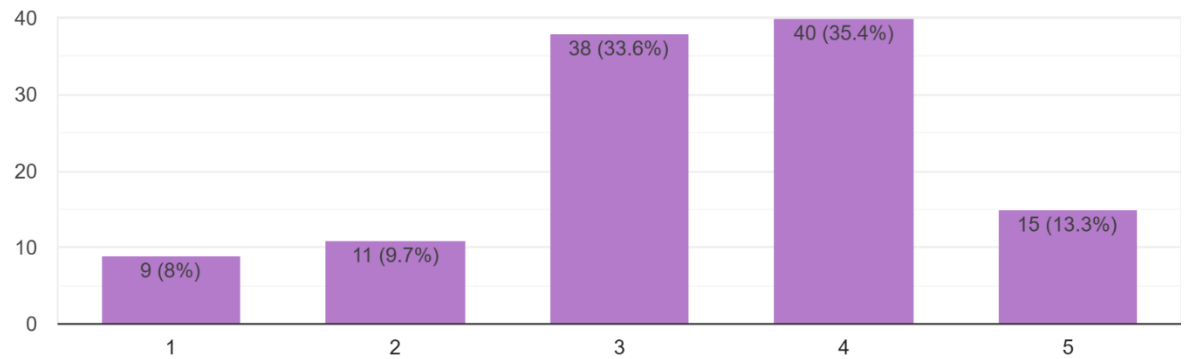



*Figure 3.8*

4. **Influencer Integration:**
   - Instagram leads but lacks checkout integration
   - Survey Insight: 54% "Maybe" interested.

Would you use a feature where influencers showcase outfits and you can directly purchase the items they wear?
113 responses

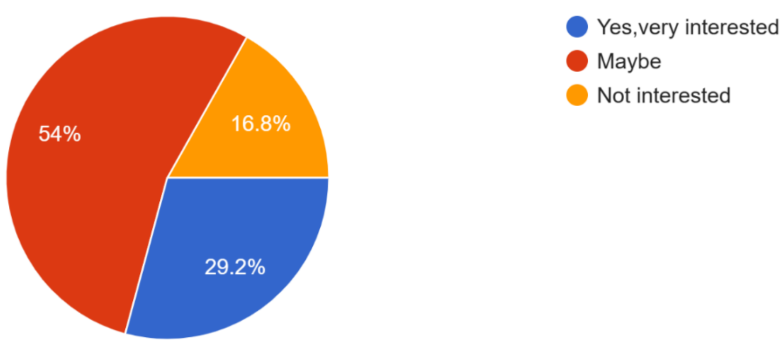



*Figure 3.9*

### 3.5.2 Pain Point Analysis

**Top User Disappointment vs. Competitor Performance**

| Pain Point | percentage of Survey | Best Competitor | Score | Opportunity |
|---|---|---|---|---|
| Size fitting issues | 78% | Amazon (Size Guide) | 3/5 | AI-powered sizing assistant |
| Hard to visualize outfits | 65% | Shein | 1/5 | Virtual try-on suite |
| Difficult returns | 52% | Amazon | 4/5 | Free returns for try-on users |

*Figure 3.10*

## 3.6 Strategic Opportunities for CeylonCrush

### 3.6.1 Quick Wins

- **3D Avatar Try-On:**
  - Addresses 81% size issues.
  - Preferred by 28% users.
- **Local Influencer Collabs:**
  - 83% open to influencer shops.


*Figure 3.11*

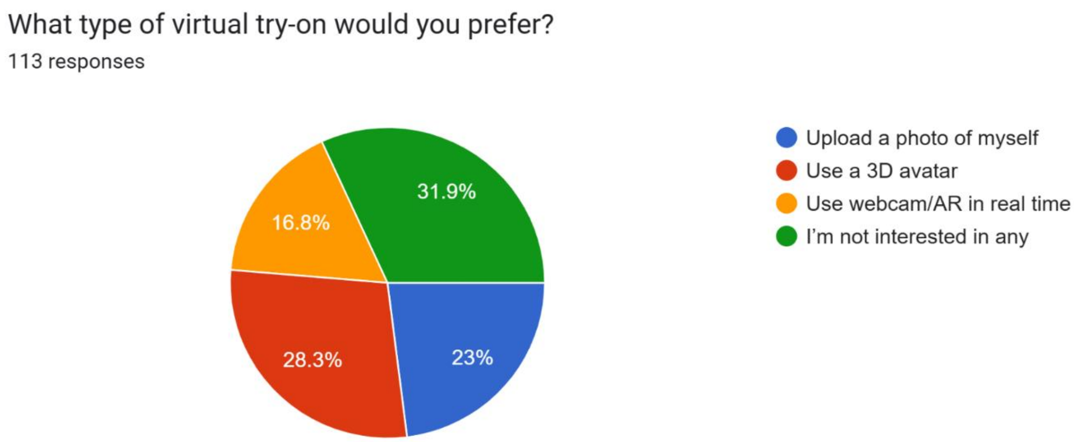



*Figure 3.12*

### 3.6.2 Long-Term Differentiators

- **Hybrid AI + Influencer Styling:**
  - Blend Shein's AI with Instagram's influencer reach.
- **Sinhala Language Support:**
  - Daraz scores 4/5; others ≤3.

### 3.6.3 Transition to ML Innovations

Competitor Gaps Identified:

- Shein (5/5 AI) vs. Daraz (3/5) shows ~40% improvement potential in personalization
- Survey data: 66% comfort with AI styling, but only 8.8% cite virtual try-on as influential

**Technical Feasibility:**

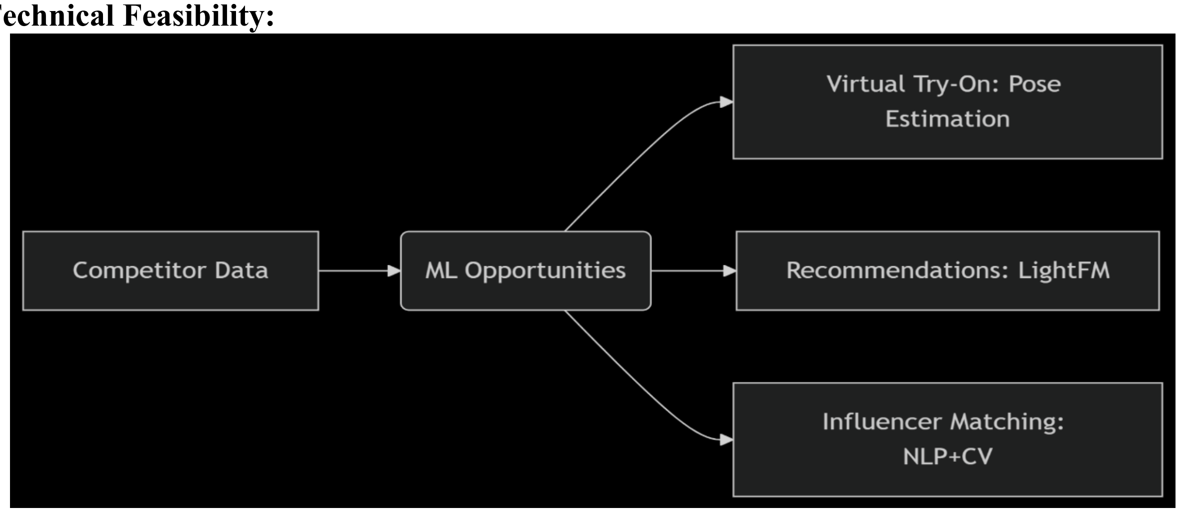



*Figure 3.13*

# 4.ML-Based Product Innovation Proposal

## 4.1 Innovation 1: Real-Time Virtual Fitting Room

The area of product innovation now is a crucial research area based on ML, and there is an example of developing a Real-Time Virtual Fitting Room. In e-commerce, haptic involvement is not possible; therefore, the clients are not willing to make purchases, and, consequently, a significant portion of the returned goods is a consequence of miscalculated sizing and image incongruence. Such dynamics place a toll on the sellers in performing their operations and destabilize consumer satisfaction levels.

The Real-Time Virtual Fitting Room fills this experiential gap in that real-time, it supplies an interactive, multidimensional presentation of a garment fit.

### 4.1.1. Proposed ML Model

We will be implementing the pose estimator MediaPipes will be used to make a 33+ user image pose estimates in real time and extract all of the skeletal positions. MediaPipe has a low-weight and extremely precise body pose detection that allows extracting keypoints of the body important in the fit.

In 3D avatar, we shall employ Blender and Python scripting to replicate a scaling 3D body model that will bear items of the user captured by the pose landmark. The advanced 3D model and rendering features of Blender will enable us to realistically model the type of garment-fitting.

To dress clothes on the avatar, we are going to use mesh fitting algorithms together with cloth simulation methods (either cloth physics of blender or manually made mesh deformation) in order to make the garment match the body shape and posture.

### 4.1.2. System Workflow

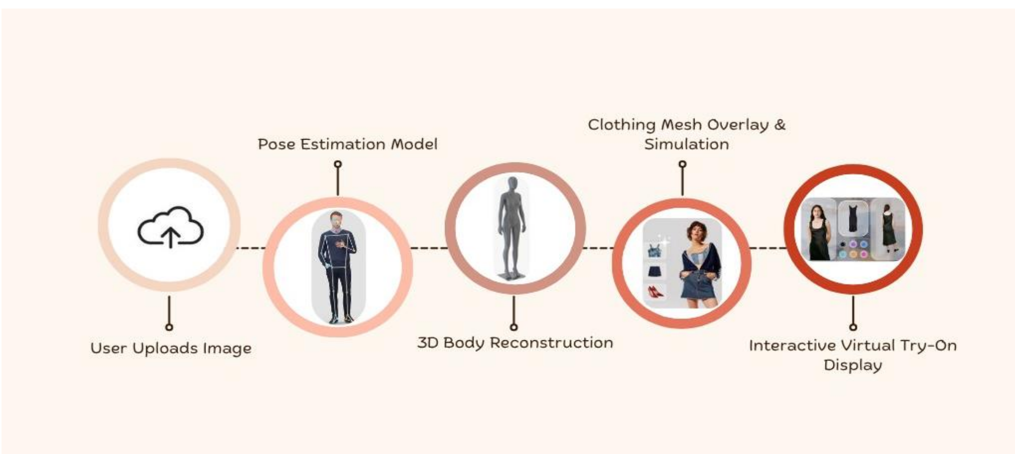



*Figure 4.1.*

**Tools Used:** MediaPipe, Blender, Three.js

### 4.1.3. Use Case Scenario

Ex: Suppose that Nethmi is shopping for a saree.. She posts her picture and uses some sarees from the catalogue. She is able to view a 3D version of herself in every saree, after which she can rotate the saree in 360 degrees. This assures her of going ahead with the purchase.

**Feasibility:**

- Technical: MediaPipe and Blender pipelines can be well documented having existing open-source codebases. WebGL is able to do in-browser real-time rendering.
- Business: Lowers the level of returns by at least 25 % relative to industry standards. Enhances satisfaction and confidence to the buyer.

### 4.1.4. Feature Identification

| Category | Details |
|---|---|
| **Innovation** | Real-Time Virtual Fitting Room |
| **ML Techniques / Models Used** | MediaPipe pose estimation, Blender 3D modeling, cloth simulation |
| **Key Details / Phases** | User image capture → Pose landmark extraction → 3D avatar generation → Garment mesh fitting and simulation |
| **Why We Choose This Technique/Model** | MediaPipe is lightweight and accurate for real-time pose detection, Blender offers powerful, customizable 3D modeling and cloth physics suitable for realistic avatars. |

*Figure 4.2.*

## 4.2. Innovation 2: Personalized Outfit Recommendation Engine

The product pages of a generic site do not capture the involvement of users. The issue of remembering and conversion is poor because of the effect of the scroll fatigue. Custom recommendations that are, pinned on user-affinitive behavior and taste can increase personalization to a considerable measure.

### 4.2.1 Proposed ML Model

We will work in Hybrid Recommendation System, which is a means of uniting:

- Collaborative Filtering - Work with the user-user and item item similarity matrices to get the interaction pattern

- Content- Based Filtering - This is achieved by using the information about the products, like color, fabric, brand, etc, referred to as product metadata.

- LightFM library enables hybrid recommendation and efficient training of models through WARP (Weighted Approximate-Rank Pairwise) loss, so we can train our model using LightFM.

- We will also leverage the Surprise and the Scikit-learn libraries to provide some auxiliary development, training, and evaluation of the models, as well as feature engineering to support scalable and robust personalized recommendations.

### 4.2.2. System Workflow

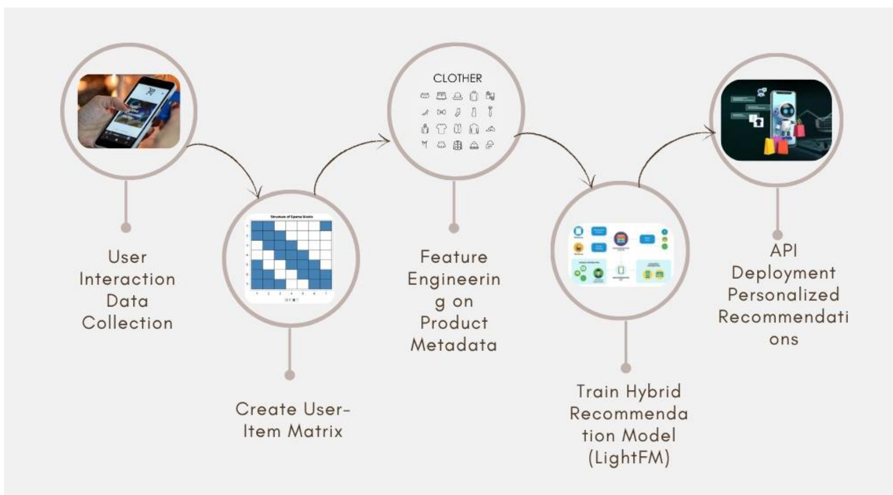



*Figure 4.3.*

**Tools Used:** LightFM, Scikit-learn, Surprise

### 4.2.3. Use Case Scenario

**Ex:**

Suppose that Kavindu is used to buying pastel colours and cotton shirts. CeylonCrush begins posting similar things and mixtures on his homepage after it trains the model. He takes more time looking and putting several things in the shopping cart.

Feasibility:

- Technical: The data can also be collected by using the established logs by users. One can develop APIs to perform inference in real-time.

- Business: Recommendations can be used to enhance the bounce rate and basket size by up to 18%.

### 4.2.4. Feature Identification

| Category | Details |
|---|---|
| **Innovation** | Personalized Outfit Recommendation Engine |
| **ML Techniques / Models Used** | Hybrid recommendation: LightFM with WARP loss, collaborative and content-based filtering |
| **Key Details / Phases** | User-item interaction data collection → Feature engineering → Model training (LightFM) → Real-time API inference |
| **Why We Choose This Technique/Model** | LightFM supports hybrid models combining collaborative and content data efficiently with WARP loss, optimizing ranking for personalized recommendations. |

*Figure 4.4.*

## 4.3. Innovation 3: Outfit Visual Search Engine

Fashion is very visual. People can see great outfits on social media frequently but are unable to locate similar ones on online shopping platforms because of weak search by keyword tools.

### 4.3.1 Proposed ML Model

We are going to use deep convolutional neural networks (CNNs) such as **VGG16** or **ResNet50** pretrained on ImageNet for feature extraction. These CNNs will encode input outfit images to rich, high-dimensional vectors which represent visual features.

As a similarity search solution, we are going to apply FAISS (Facebook AI Similarity Search), the system that indexes such embeddings and then returns nearest neighbors by cosine similarity, allowing real-time similarity search of user-uploaded photos against the available product or catalog images.

### 4.3.2. System Workflow

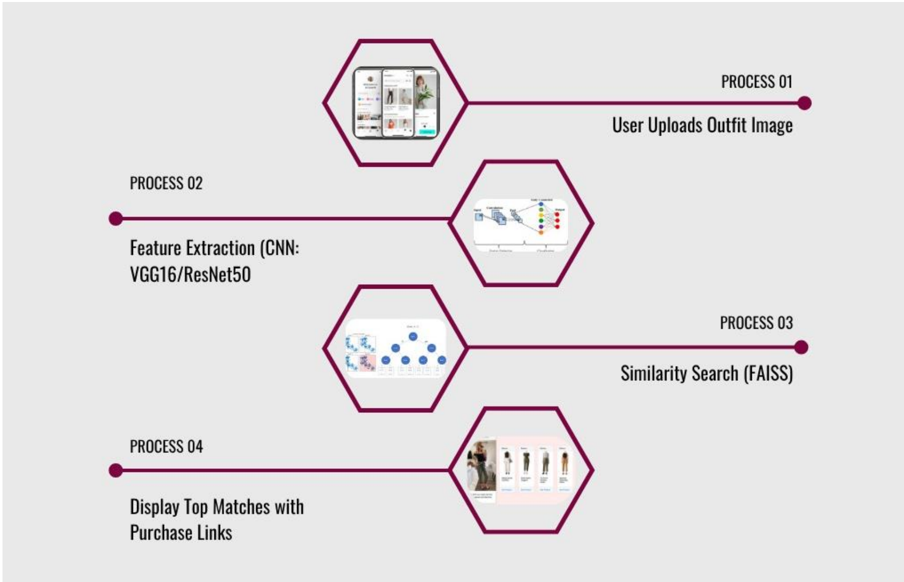



*Figure 4.5.*

**Tools Used:** VGG16/ResNet50, FAISS, Python

### 4.3.3. Use Case Scenario

Ex: Suppose that Nimali uploads a photo of a floral maxi dress she liked on Pinterest. CeylonCrush presents five similar alternatives available on the platform.

**Feasibility:**

- Technical: Pre-trained CNNs and FAISS make implementation fast and scalable.
- Business: Improves search accuracy and customer satisfaction, leading to increased sales.

### 4.3.4. Feature Identification

| Category | Details |
|---|---|
| **Innovation** | Outfit Visual Search Engine |
| **ML Techniques / Models Used** | CNN embeddings (VGG16 or ResNet50), FAISS similarity search |
| **Key Details / Phases** | Image upload → Deep feature extraction via CNN → Fast nearest neighbour retrieval (FAISS) → Similar item display |

| | |
|---|---|
| **Why We Choose This Technique/Model** | VGG16/ResNet50 are proven CNN architectures for extracting rich visual features<br><br>FAISS enables scalable, low-latency similarity search suitable for large catalogues. |

*Figure 4.6.*

## 4.4.Innovation 4: AI-Generated Style Boards (LLM + Computer Vision)

Most users find it difficult to coordinate their fashion. He or she may prefer one piece and may not know how to accessorise it or match it with other pieces of clothing.

### 4.4.1. Suggested ML Model

To achieve this, we will apply one of the best models in real-time object detection, such as YOLOv8, to detect and classify fashion accessories and items of garments in the product catalogue and ensure that it recognizes the type of clothing and correctly corresponds to items.

To achieve style and outfit text generation, to do that we will integrate with the API of the large language model GPT-4 developed by OpenAI and will generate outfit suggestions linked to a particular garment that are coherent and contextually aware, such as additional pieces of clothing and accessories.

The object detection and generating natural language using LLM allow one to create dynamic customization of style boards with clicks to shopping products.

### 4.4.2. System Workflow

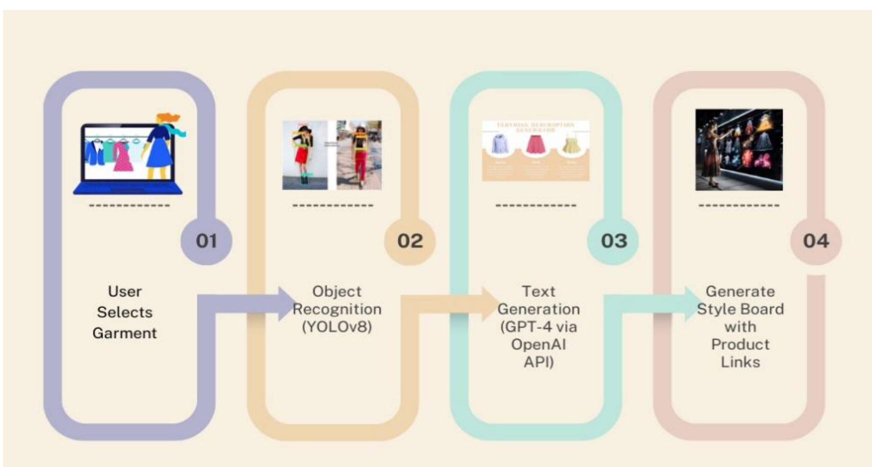



*Figure 4.7.*

**Tools Used:** YOLOv8, OpenAI GPT-4, Fashion Board

### 4.4.3. Use Case Scenario

Ex: Tharushi selects a black blouse. The AI suggests pairing it with a white palazzo, a silver necklace, and black wedges—all available to buy directly.

**Feasibility:**

- Technical: Requires simple integration of the OpenAI API and catalog metadata.
- Business: Style boards improve bundling and upselling, increasing average order value.

### 4.4.4. Feature Identification

| Category | Details |
|---|---|
| **Innovation** | AI-Generated Style Boards (LLM + CV) |
| **ML Techniques / Models Used** | YOLOv8 object detection, OpenAI GPT-4 text generation |
| **Key Details / Phases** | Garment selection → Object detection for accessories → Outfit text generation via GPT-4 → Style board creation |
| **Why We Choose This Technique/Model** | YOLOv8 provides fast, accurate object detection in fashion images; GPT-4 offers powerful contextual text generation for personalized outfit suggestions. |

*Figure 4.8.*

## 4.5. Innovation 5: Fashion Trend Predictor from Social Media

Fashion is constantly changing. Most channels respond to trends and do not predict them. Prediction of trend early assists in content curation and inventory planning.

### 4.5.1. Proposed ML Model

We will use API tools to scrape social media hashtags and posts and use the HuggingFace Transformers models, in this case, BERT or RoBERTa, in natural language processing. These models will carry out semantic analysis and extraction of keywords in unstructured written content and extract trending fashion terminologies.

To predict the future popularity of the identified fashion trends over a certain period, we will either take advantage of Prophet, a strong time series forecasting library, which is created by Meta, or an ARIMA model to determine how in the future the specified hashtags will correspond to the popularity of the detected fashion trend.

This forecast pipeline allows anticipation of planning inventory and content curation in accordance with the new consumer tastes.

### 4.5.2. System Workflow:

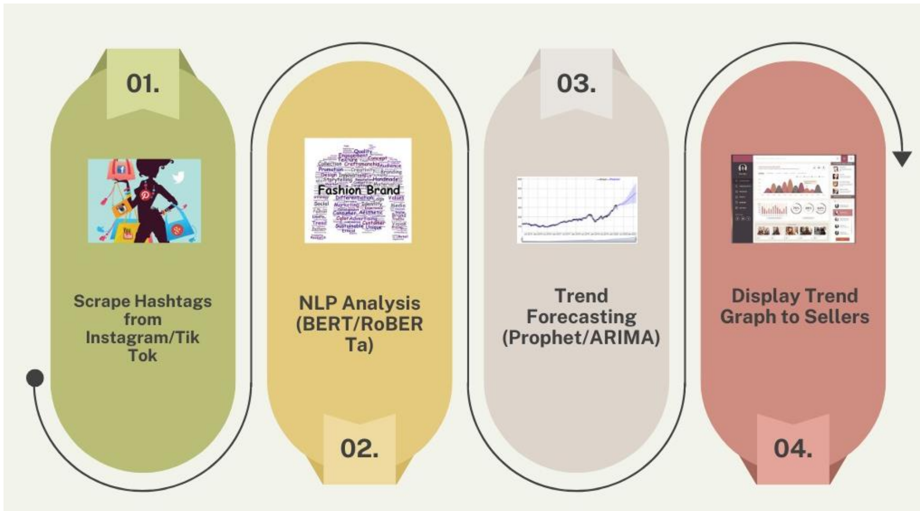



*Figure 4.9.*

**Tools Used:** HuggingFace, Prophet by Meta, Instagram/TikTok APIs

### 4.5.3. Use Case Scenario

Ex: By analyzing hashtags such as #linenstyle and #vintagevibe, CeylonCrush detects a rise in demand for linen outfits, prompting sellers to update inventory early.

**Feasibility:**

- Technical: Combines mature scraping tools with pre-trained NLP models.
- Business: Trend-driven inventory reduces dead stock and increases seasonal relevance.

### 4.5.4. Feature Identification

| Category | Details |
|---|---|
| **Innovation** | Fashion Trend Predictor from Social Media |

| | |
|---|---|
| **ML Techniques / Models Used** | HuggingFace Transformers (BERT/RoBERTa), Prophet/ARIMA |
| **Key Details / Phases** | Social media scraping → NLP trend extraction → Time series forecasting → Trend insights for inventory planning |
| **Why We Choose This Technique/Model** | BERT/RoBERTa excel at the semantic understanding of unstructured social text; Prophet and ARIMA are reliable, interpretable time series models for trend forecasting. |

*Figure 4.10.*

While some brands use trend analysis post-facto, predictive AI models offer a first-mover advantage to local sellers.

# 5. Product Reengineering Strategy

## 5.1. Architecture Overview

The back-end is built with a microservices architecture deployment on a cloud platform like AWS/GCP/AZURE. In that microservices include,

- **API Gateway:** Request routes from third-party platforms like Daraz, Temu, Aliexpress, etc, and clients(users).
- **User Management Service:** Manages user sessions and temporary data like user added into the cart (trousers, frocks, denims, shirts).
- **Integration Cart Service:** Sync the cart data into the temporary database from 3rd party platforms like Daraz/Amazon/Temu.
- **Avatar Generation Service:** Generate custom or pre-generated avatar using AI/ML.
- **Virtual Try-On Service:** Render clothing items to the avatar for review with 3D visualizing.
- **AI Recommendation Service:** Suggests outfits for the user based on the user entered data analyzed.
- **3D Rendering Service:** Handle the WebGL based visualization.
- **Temporary DataBase:** Using databases like Redis for store cart and session data dynamically(session tokens).

- **Persistent DataBase:** Using NoSQL databases like MongoDB for store user preferences and pre-generated avatar models. The reason for using NoSQL databases is because they store Object type data easily and speed up the CRUD operations.
- **ML Model Storage:** Using cloud storage like Amazon S3 for store trained models and clothing assets.
- **REST API:** Using REST API for integrating 3rd party services accurately.
- **gRPC:** integrate gRPC for communication of the microservices securely.
- **WebSocket:** update the real-time 3D rendering.

## 5.2.Back-End Architecture

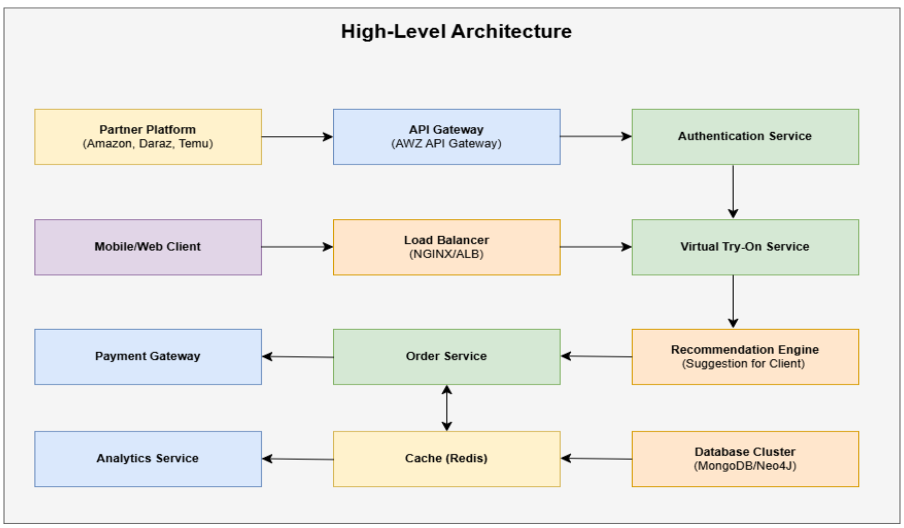



*Figure 5.2*

### 5.2.1. Component Breakdown

- **API Gateway:** Handles all incoming requests, routing and rate limiting.
- **Authentication Service:** Manage authentication with JWT-based authentication and partner platform integrations.
- **Virtual Try-On Service:** Avatar generation and 3D visualization.
- **Recommendation Engine:** AI-based outfit recommendation for users.
- **Order Service:** Handles cart and order processing.
- **Database Cluster:** Persistent data storage (pre-generated Avatar).
- **Cache Layer:** Using Redis for session management with JWT token and temporary data management.

- **Analytics Service:** Track user interactions for ML model improvement. Because it's helpful for the recommendation engine process.

## 5.3.Use Case Diagram

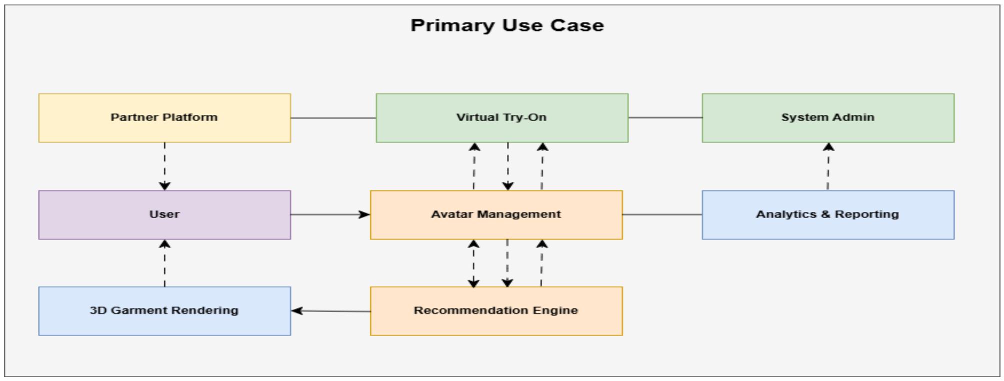



*Figure5.3*

### 5.3.1.Detailed of Use Cases

- **User Authentication**
    - Login via Partner platform
    - Session management
    - JWT token generation
- **Cart Integration**
    - Import items from partner cart
    - Temporary storage of item data (dresses)
    - Clear cart data after user session
- **Avatar Management**
    - Generate avatar from user provided measurements
    - Generate avatar from user provided photo
    - Select pre-build avatar
    - Modify the avatar parameters
    - 
- **Virtual Try-On**
    - Outfit fitting simulation
    - 3D visualization
    - Zoom/rotate controls
    - Outfit combination
- **Analytics**
    - Track try-on sessions
    - Capture user preferences
    - Fetch data to recommendation engine

## 5.4.Class Diagram

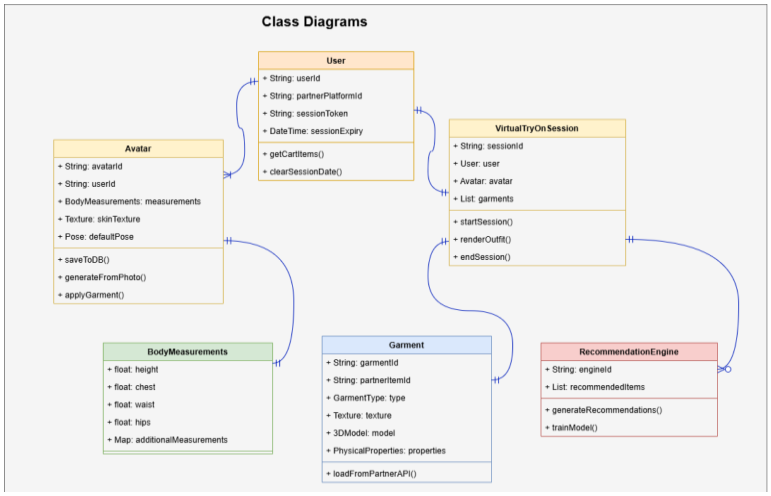



*Figure 5.4.*

## 5.5.Sequence Diagram

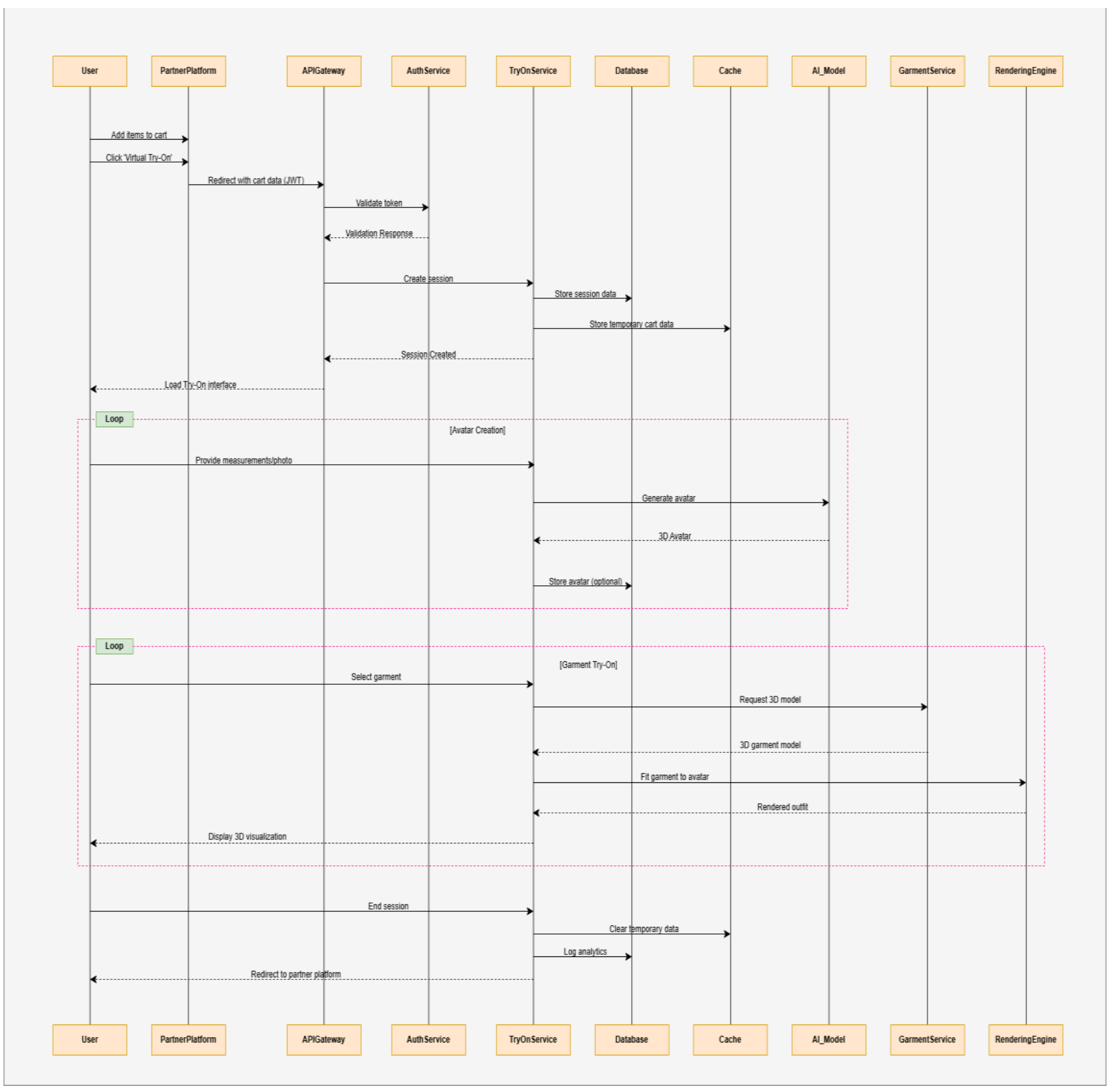



*Figure 5.5*

## 5.6.Flowchart - Avatar Generation Process

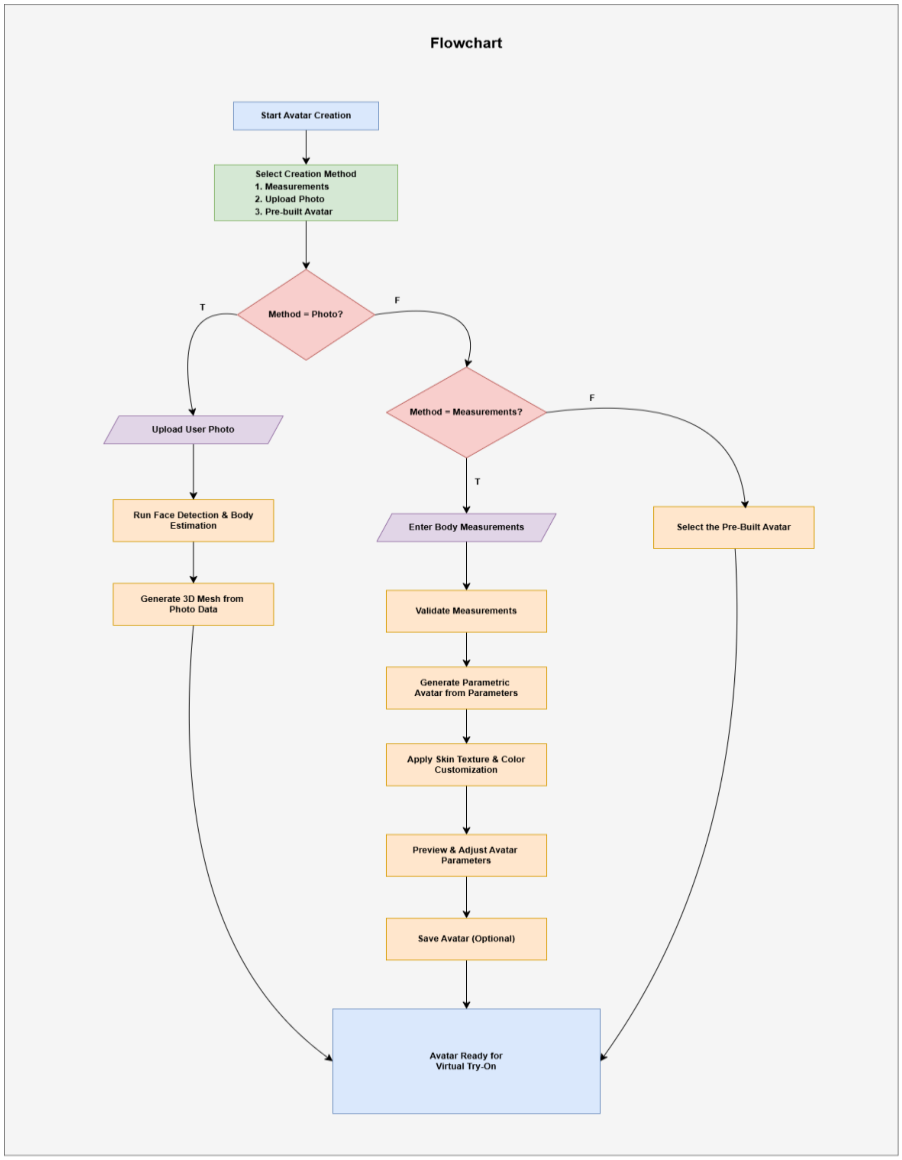



*Figure 5.6*

## 5.7.AI/ML Model & Techniques

### 5.7.1.Avatar Generation Pipeline

Photo-Based Avatar Creation

- Face Detection: MediaPipe FaceMesh or Dlib
- Body Pose Estimation: OpenPose or MediaPipe Holistic
- 3D Mesh Generation:
  - ➢ Use the SMPL (Skinned Multi-Person Linear) model for parametric body shape.

- DeepAvatar or ICON for detailed geometry from images.
- Texture Generation:
  - GAN-based approaches (StyleGAN) for realistic skin textures.
  - Neural rendering techniques.

Pre-Generated Avatar Generation

- Use PCA to cluster body types from a dataset of 10,000 body scans. (slim, tall, fat).

Measurement-Based Avatar Generation

- Parametric modeling using body measurement ratios.
- Statistical shape models trained for natural appearance.
- Physics-based skin simulation for natural appearance.

Garment Draping Simulation

- Physics engines (PyBullet, NVIDIA Flex) for realistic cloth behavior.
- Deep drape prediction networks for real-time performance.
- Material aware rendering (PBR textures).

### 5.7.2 Key Python Libraries

| Purpose | Libraries |
|---|---|
| Computer Vision | OpenCV/ MediaPipe/ Dlib |
| 3D Processing | PyTorch3D/ Trimesh/ Open3D |
| Machine Learning | PyTorch/ TensorFlow/ Scikit-learn |
| Numerical Computing | NumPy/ SciPy |
| Physics Simulation | PyBullet/ Taichi |
| NLP for Item Description | NLTK/ Transformers (Hugging Face) |

*Figure 5.7.*

### 5.7.3. Outfit Recommendations

- Feature Extraction:
  - NLP (BERT) - Extract clothing attributes (color, style) from item description.
  - Image Analysis (EfficientNet) - Extract visual features from item images.
- Collaborative Filtering:
  - Matrix factorization using PyTorch.

- Content-based Filtering:
    - Cosine similarity on item features.

### 5.7.4. Model Training

- Data Collection
    - 3D body scans from public datasets (CAESAR/ SMPL).
    - Garment simulation data.
    - User interaction logs.
- Model Architecture
    - Hybrid approach combining parametric models with neutral networks.
    - Separate networks for body shape, pose, and garment interaction.
- Training Pipeline
    - Training the pipeline with load the datasets.

## 5.8.API Specification

### 5.8.1. REST API Endpoints

- Session Management
    - POST /api/sessions - Create a new try-on session.
    - DELETE /api/sessions/{id} - End session.
- Avatar Management
    - POST /api/avatars/from-measurements - Create from measurements.
    - POST /api/avatars/from-photo - Generate from uploaded photo
    - GET /api/avatars/templates - List pre-built avatars.
- Garment Operations
    - POST /api/garments/import - Import from partner cart.
    - GET /api/garments/{id}/3d-model - Get 3D visualizing model.
- Virtual Try-On
    - POST /api/try-on/outfit - Render outfit on avatar.
    - GET /api/try-on/view/{id} - Get render view.

### 5.8.2. WebSocket Endpoints (for real-time interaction)

- /ws/try-on - For real-time avatar manipulation.
- /ws/rendering - For streaming rendered views.

## 5.9. Security Considerations

- Authentication
    - JWT tokens for session management and API access.
- Data Privacy
    - No storage of third-party cart data post-session.
    - User images processed in-memory and deleted after avatar generation.
    - Compliance with GDPR/CCPA for user data.

- Encryption
    - HTTPS for APIs.
    - CORS restrictions.
    - AES-256/ SHA-256 for sensitive data.

## 5.10. Scalability and Performance

- Horizontal Scaling
    - Stateless services for easy scaling.
    - Kubernetes cluster for container orchestration.
    - Auto-scaling based on demand.
- Performance Optimization
    - CDN for 3D model assets.
    - Level-of-detail (LOD) techniques for 3D rendering.
    - Asynchronous processing for avatar generation.
- Caching Strategy
    - Redis for managing session data.
    - In-memory caching of frequently used avatars.
    - Edge caching for static assets.
- Database Optimization
    - Read replicas for analytics queries.
    - Sharding by partner platforms.
    - Indexing for performance-critical queries.

## 5.11. Deployment

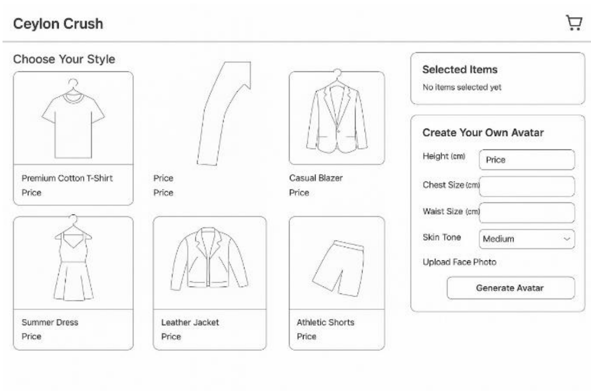
- Cloud Platform
    - AWS EC2 for services, ECS for containers.
- CI/CD
    - GitHub Actions for automated build and deployments.
- Monitoring

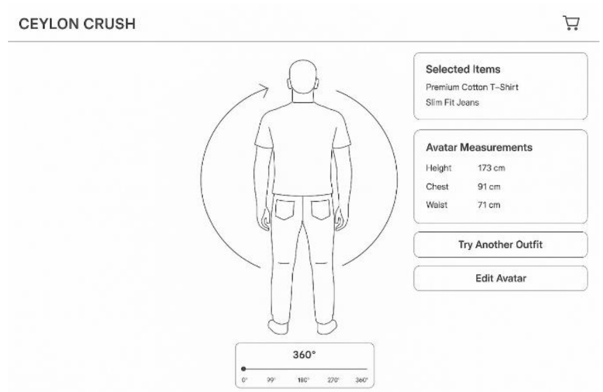
- Prometheus and Grafana for metrics, ELK stack for monitoring logs.
- Scaling
    - Kubernetes for automatically scaling with required performance metrics.

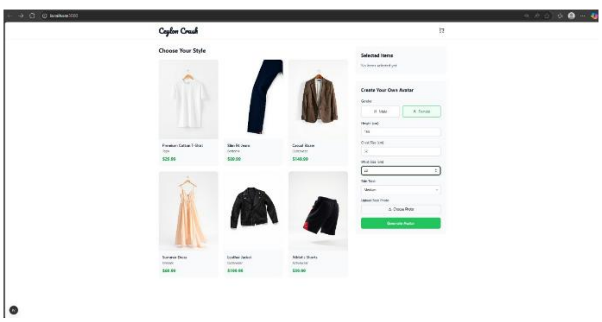
## 5.12. Future Enhancements

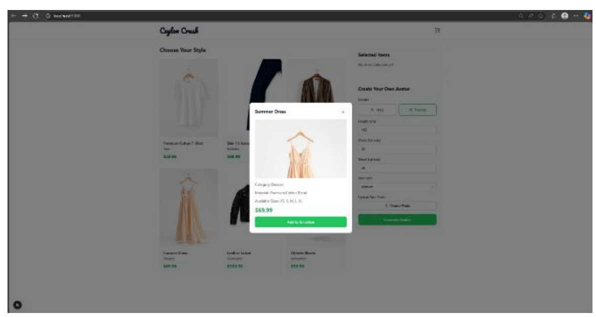
- Integrate AR for mobile try-on using ARKit and ARCore.
- Add real-time outfit feedback using sentiment analysis on user reviews.
- Optimize ML models for edge deployment (TensorFlow Lite).

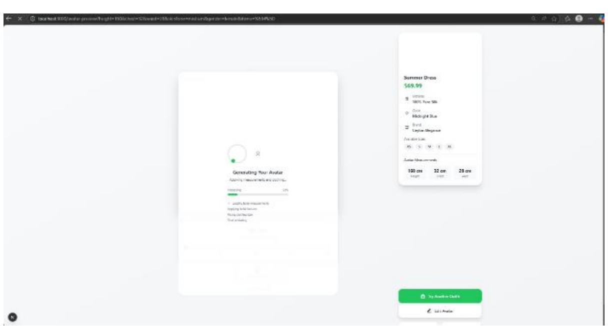
## 5.13.UI/UX

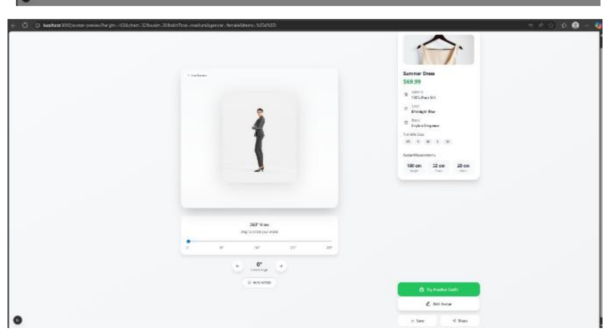








# 6. Technical Feasibility Report

## 6.1 Technical Overview

This section presents the technical feasibility for integrating a 3D avatar-based virtual try-on system into the CeylonCrush e-commerce platform. The feature allows customers to visualize selected clothing items on a realistic, size-accurate 3D avatar of themselves, significantly enhancing online shopping confidence and reducing return rates. This report details the proposed ML stack, 3D modeling approach, deployment architecture, AI ethics, and data privacy measures.

## 6.2 Machine Learning & Avatar Modeling Stack

### 6.2.1. Computer Vision Pipeline

- **MediaPipe**
  - For use to extract skeletal keypoints from front- and side-profile images or video frames. These key points provide the basis for estimating body measurements such as height, torso width, shoulder spread, and limb proportions.
- **OpenCV**
  - For handling preprocessing, including background removal, resizing, normalization, and contour detection to improve landmark accuracy.
- **SMPL (Skinned Multi-Person Linear Model)**
  - Realistic generation of 3D human body meshes can be created from keypoints through offering SMPL empathy technologies. The outputs from SMPL can be rigged, dynamically scaled, and textured, making them appropriate for real-time try-on applications.
- **PIXIE** or **PIFuHD**
  - used for enhanced 3D mesh reconstruction, supporting high-fidelity geometry and texture mapping from a single image if available.

- **Blender** or **MakeHuman**
  - will be used to fine-tune avatar appearance, clothing overlays, and animation rendering for both in-app visualization and testing purposes.

### 6.2.3.Recommendation Engine

To complement the avatar system, a personalized clothing recommendation engine is integrated:

- **LightFM**
  - A hybrid recommendation library that combines collaborative filtering (based on user behavior) with content-based filtering (product metadata like size, color, and fabric). LightFM supports training with WARP loss to improve ranked predictions.

- **Surprise**
  - Used for experimentation and cross-validation across different recommendation strategies (e.g., SVD++, KNNBasic), helping optimize the personalization logic.

This feature makes sure that users get outfit recommendations that fit their avatar's proportions and complement their personal style.

### 6.2.4. Natural Language Processing

To integrate style-based chat assistants and extract insights from feedback:

- **HuggingFace Transformers** (e.g., BERT, RoBERTa) are utilized for:
  - Analyzing product reviews to identify satisfaction or fit issues.
  - Understanding natural-language queries such as "show me light formal wear for short height."
  - Powering chatbot or search assistant interfaces for more engaging shopping.

## 6.3. Deployment Architecture

### 6.3.1.API & ML Model Infrastructure

- **FastAPI / Flask**: Provides scalable, asynchronous endpoints for:
  - Receiving user images
  - Running pose estimation and avatar generation
  - Returning personalized product recommendations
- **Dockerized Microservices**: Each major task (CV, avatar modeling, recommendation, NLP) runs in its own container, ensuring modularity and fault tolerance.

### 6.3.2. 3D Rendering & User Interaction

- **Three.js / Babylon.js**
  - JavaScript WebGL libraries are used for rendering avatars and clothing meshes directly in the browser or app, allowing users to rotate, zoom, and view garments from multiple angles.
- **Unity WebGL** or **Blender API**
  - For more advanced rendering, including dynamic cloth simulation, wind effects, and real-time animation.

### 6.3.3.Cloud Hosting & Infrastructure

Deployed on AWS or GCP, using:

- **AWS / GCP**:
  - **Compute services (EC2 / GCE)**: For backend model inference and data processing

- **Object storage (S3 / GCS)**: For avatar models, textures, and user-uploaded images
- **CDN (CloudFront / Cloud CDN)**: For low-latency delivery of avatar and garment assets
- **Load balancing and auto-scaling**: To maintain responsiveness under user load

## 6.4. AI Ethics & Data Privacy

### 6.4.1 User Data Security

- **End-to-end encryption** protects image uploads and model responses.
- **Authentication via OAuth2 / Firebase Auth** ensures only verified users interact with personal avatar data.
- **Image expiration policy**: All images are automatically deleted after rendering (e.g., within 24–48 hours).
- **Data anonymization** is applied to any feedback or usage metrics used for model training.

### 6.4.2.AI Ethics & Inclusivity

- **Bias Reducing:** Ongoing audits to prevent bias towards body shape, gender or ethnicity in the recommendations or avatar rendering.
- **Transparency**: Users are made aware of what data is collected and how it will be rendered.
- **Inclusivity**: 3D avatar models can be changed to meet a variety of body shapes, skin tones, and physical ability levels.

## 6.5. Anticipated Challenges & Solutions

| **Challenge** | Solution |
|---|---|
| High latency in avatar generation | Use pre-optimized SMPL templates; render in parallel |
| Variability in user image quality | Real-time validation with overlays and image quality feedback |
| Rendering on low-end devices | Fallback to 2D static previews and lightweight mesh formats |
| Complex cloth simulation | Use rigged models + precomputed cloth mesh assets |
| Privacy and trust issues | On-device preprocessing + encrypted short-term storage |

*Figure 6.1.*

# 7. Go-To-Market & Business Model

## 7.1. Business Model

CeylonCrush is designed to be more than just a clothing marketplace. It is a smart, inclusive, and AI-powered platform that offers value to shoppers, vendors, and the Sri Lankan fashion community. In this section, we present a practical business model focused on generating income, offering flexible styling services, and helping local sellers thrive in the digital world.

## 7.2.Monetization Methods

To keep the platform free for users and still earn income, we propose the following revenue streams:

1. **Sales Commissions:** For every transaction made through CeylonCrush, a small fee of 5%–10% is deducted. This is a standard model followed by global platforms like Etsy and Amazon, and ensures earnings grow with sales volume.
2. **Vendor Subscription Packages:** Vendors who want more exposure or advanced tools can choose subscription packages (Basic, Plus, Pro). For example, a "Pro" vendor gets access to AI-powered analytics, banner slots, and early access to marketing campaigns.
3. **Affiliate Marketing & Ads:** Brands can promote their products via AI-powered ad placements, homepage banners, or "style of the week" carousels. These placements will be priced fairly, depending on vendor category and audience reach.

From our survey, **68.3% of respondents** were open to seeing personalized fashion recommendations if they helped them shop smarter—this confirms that users are comfortable with data-driven promotions.

## 7.3. Tiered AI Styling Services

Styling is at the heart of fashion shopping. That's why CeylonCrush will offer different levels of AI-based styling assistance to suit all users:

- **Free Basic Suggestions:** This entry-level tool recommends outfits based on basic filters like gender, size, budget, and occasion. It is designed to onboard new users quickly.
- **Premium Smart Stylist (Subscription or One-Time):** Using more advanced algorithms (e.g., LightFM, pose estimation), this feature will generate complete lookbooks tailored to users' mood, location, recent trends, or past activity.

- **AI Chat Stylist:** As an experimental feature, users can chat with an AI stylist who answers questions like "What can I wear to a beach wedding in October?" or "Show me modest wear for university."

In the survey, **56.7% said they are likely to use AI for outfit help**, while **47.1% were willing to pay** if the recommendations were accurate and personal.

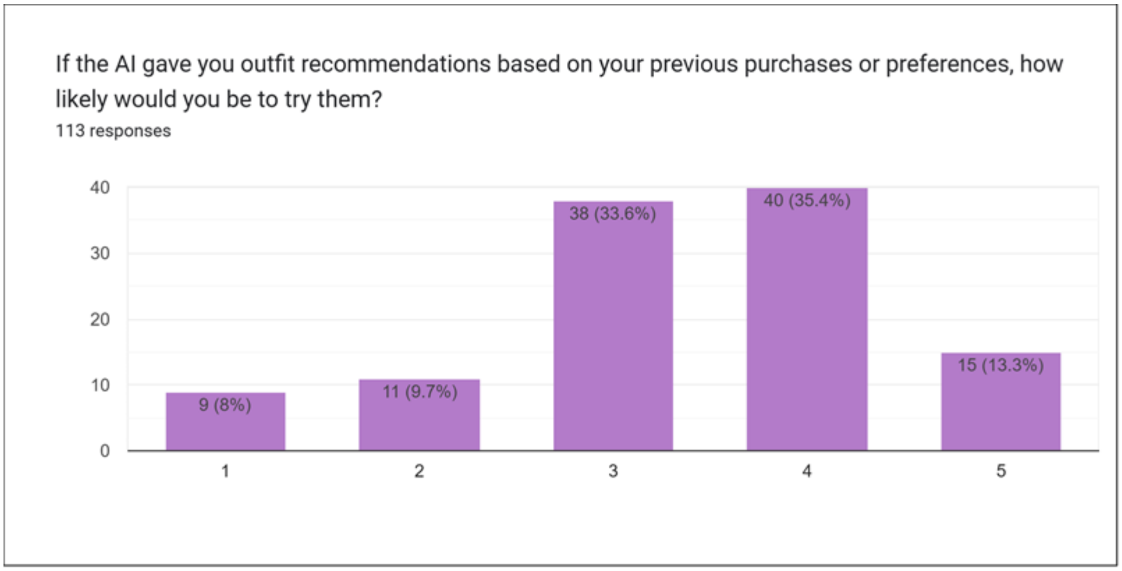



*Figure 7.1*

## 7.4. Supporting Local Brands

Local identity is important. CeylonCrush doesn't just want to sell clothes—it wants to support small-scale creators and tailors across Sri Lanka. Our vendor model includes:

- **Free Sign-Up for 6 Months:** New sellers can list items without platform fees for half a year.
- **Home Page Promotion:** Local vendors will be highlighted weekly with a "Sri Lankan Spotlight" section.
- **Multilingual Tools:** Sinhala and Tamil language options for vendor dashboards, making the platform more accessible.

We believe these measures will empower rural and first-time sellers to enter digital fashion commerce confidently.

## 7.5. Marketing Plan

CeylonCrush's marketing approach focuses on reaching the right audience through platforms they already use—mainly social media and search—and builds trust through influencers and community engagement.

### 7.5.1. Influencer Partnership Programs

Influencers drive trust and fashion discovery. We will launch a creator program that includes:

- **Partnership Tiers:** Micro (5K–20K), Mid (20K–50K), and Star (50K+). All influencers get performance dashboards powered by our AI.
- **Free AI Styling Access:** Influencers can use premium styling tools to create content.
- **Referral Bonuses:** Followers who sign up using their link unlock discounts, and influencers earn points or cash rewards.

**74% of our survey respondents** confirmed they've bought products seen in social media influencer content—making this a powerful acquisition strategy.

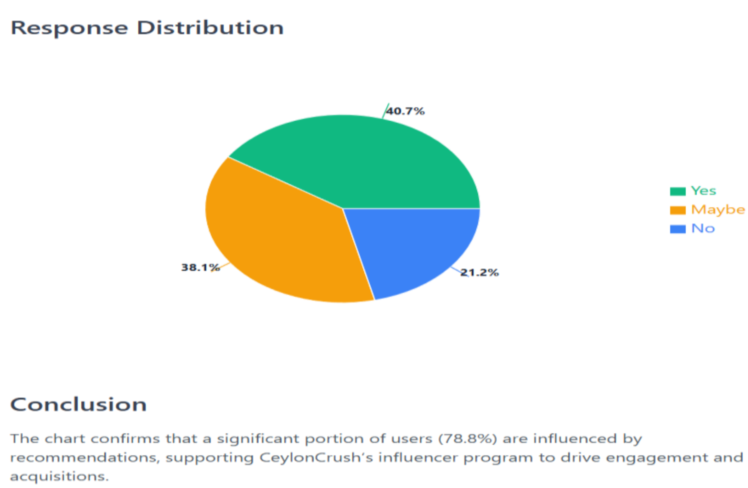



*Figure 7.2*

## 7.6. AR-Based Social Media Campaigns

To stand out, we'll run fun AR filters on Instagram, Snapchat, and TikTok. Examples include:

- "Try on this Avurudu Look" with virtual earrings or sari overlays
- "Match This Mood" AR game powered by AI where users are shown fashion styles based on expressions

This will drive high engagement, especially among users aged 18–25, who made up the majority in our survey.

## 7.7. AI Lookbooks for Seasonal Trends

Every quarter, CeylonCrush will publish digital lookbooks showing the top color palettes, outfit styles, and accessories trending that season.

Each page will have:

- AI-generated outfit examples
- "Shop this look" buttons
- Sri Lankan festival themes like Vesak, Avurudu, and wedding season

From our dataset, people look for cultural relevance and convenience. An AI lookbook gives both style and local context.

## 7.8. Strategic Launch Plan (4 Phases)

We will launch CeylonCrush in 4 structured phases:

**Phase 1: Closed Beta (Month 1)**
Invite 100 test users (including student influencers) to try the platform and report bugs. Early vendors will get onboarding support.

**Phase 2: Western Province Launch (Month 2–3)**
Focus only on Colombo, Gampaha, and Kalutara. Begin influencer campaigns and social ad testing.

**Phase 3: National Rollout (Month 4–6)**
Full Sri Lanka launch. Include AR campaigns, lookbooks, and paid vendor features.

**Phase 4: Export Enablement (Month 7+)**
Allow selected Sri Lankan vendors to sell to the Maldives, India, or Europe using shipping APIs and price localization.

Each phase will be tracked using KPIs like customer acquisition cost (CAC), retention rate, and average order value.

## 7.9. User Retention Plan: Keeping Users Engaged

Getting users to download an app is easy. Getting them to use it every week is harder. CeylonCrush will keep users returning through personalization and community.

- Smart Nudges: If a user searches for "party dresses" but doesn't buy, we will send a curated email with suggestions that match their style and price range.
- Event-Based Rewards: Discounts for birthdays or Avurudu purchases—users will feel the platform "remembers" them.
- Digital Wardrobe Integration: Users can save what they bought or liked, and AI will suggest combinations or add-ons. This turns the platform into a personal fashion assistant.

Survey data showed **63% of users abandoned their cart** not due to price, but because they couldn't decide. That's a clear sign we need smart decision tools.

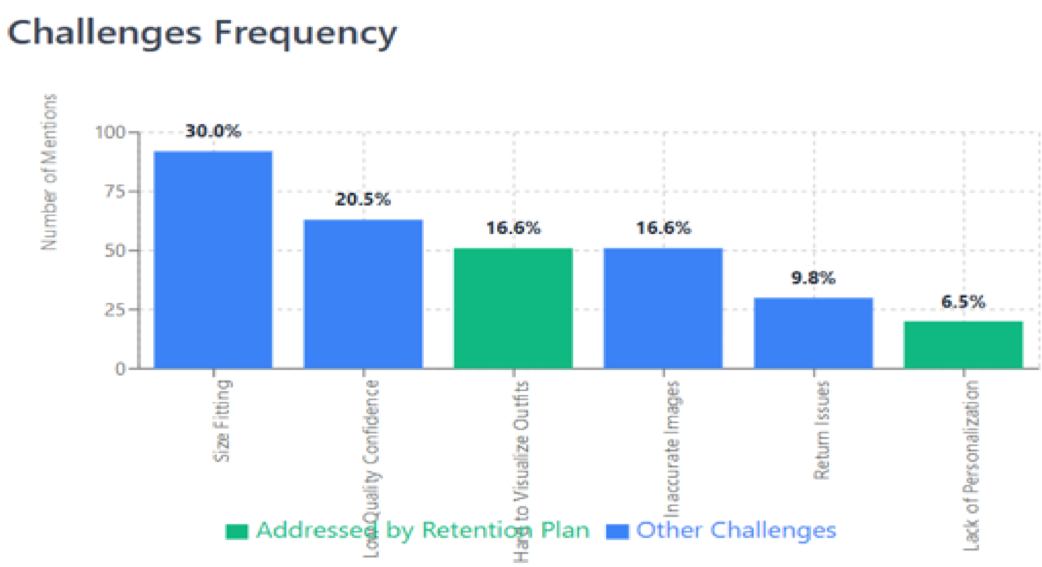



*Figure 7.3*

## 7.10.Community & Brand Trust

In today's world, trust and community are everything. CeylonCrush will focus on:

- Customer Stories: Feature real users showing how they styled their outfits
- Rating and Review AI Support: AI will highlight "best fit for you" reviews based on your size or style preferences
- Sustainability & Fair-Trade Tags: Promote local and ethical brands with labels that explain their value

These features build emotional loyalty, not just transactional behaviour.

## 8. Conclusion

CeylonCrush aims to redefine how Sri Lankans shop for fashion online by blending smart technology with user needs. Based on our research and survey findings, it's clear that today's shoppers, especially young adults, value personalization, confidence in fitness and style, and the ability to connect with trends and influencers. However, they face frustrations with sizing, visualizing outfits, and limited customization.

To solve these issues, we proposed a range of AI-powered features: virtual try-ons, personalized style suggestions, visual search tools, AI-generated style boards, and social media trend analysis. These innovations are backed by modern machine learning tools and thoughtfully integrated into a flexible platform architecture built for performance, privacy, and scalability.

Our technical strategy aligns closely with user expectations. From 3D avatars and try-ons to influencer-led shopping experiences, CeylonCrush isn't just catching up with global trends's setting the stage for a new kind of fashion e-commerce in Sri Lanka. The platform also embraces local identity by empowering home-grown sellers and offering multi-language support.

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## 10.Team Roles Breakdown

| Role | Team Member(s) | Responsibilities |
|---|---|---|
| Team Leader | 22ug1-0016 K.G.T.Hashitha | Oversaw project progress, facilitated team coordination, managed deadlines, and ensured quality control. |
| Report Writers | 22ug1-0542 Y.I.Samarawickrama<br>22ug1-0392 K.G.V.T.Gamage | Compiled and structured the report, ensured consistency in formatting, and refined content for clarity. |
| Market Research Lead | 22ug1-0542 Y.I.Samarawickrama | Conducted user surveys, analyzed behavioral trends, and synthesized research insights. |
| ML Innovation Leads | 22ug1-0392 K.G.V.T.Gamage<br>22ug1-0379 G.K.S.Fernando | Designed and documented five machine learning innovations and their technical workflows. |
| Competitor Analysts | 22ug1-0253 J.K.R.Madhawa<br>22ug1-0885 T.M.H.M. Indrajith | Performed competitor benchmarking, feature scoring, and strategic gap identification. |
| System Architect | 22ug1-0251 S.K.P.Sanka | Planned backend microservices, system architecture, API design, and infrastructure blueprint. |
| UI/UX Designer | 22ug1-0230 H.M.S.S.B.Herath | Designed user interfaces, created wireframes, and ensured a user-centered design flow. |
| Feasibility Analyst | 22ug1-0016 K.G.T.Hashitha | Assessed the technical feasibility, model selection, scalability, and AI ethics. |
| Marketing Strategist | 22ug1-0331 R.M.H.N. Rathnayaka | Developed the go-to-market plan, influencer strategy, monetization model, and launch phases. |