Novel AI Model for Evaluating Buyers' Fulfilment with Clothing Fit

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Online merchants must make sure that their customers are satisfied with the fit of their products, yet standard size charts sometimes fall short of accounting for the wide variety of body types and preferences. This research presents a novel artificial intelligence (AI) model that aims to precisely assess buyers' fulfillment with clothing fit (BF-CF). The consumer data collection was gathered. Then, we utilize the Min-max normalization for pre-processing, and principal component analysis (PCA) for feature extraction. As test clothes, skirts composed of various textiles were utilized. The BF-CF was estimated by assigning predictor factors to the mechanical characteristics of the skirt textiles. Using a 3D body scanner, virtual body models of the study participants were produced and utilized for virtual fitting. Each participant evaluated how well the clothes fit after trying them on in person. Additionally, participants evaluated the virtual fit, which indicated how well they fulfilled the virtual fit (PVFF), by looking at the skirt simulations on their avatars. The data was warmed up to predict BF-CF using a novel machine learning technique called Tabu search optimized smooth linear logistic regression (TSO-SLLR). According to the experimental data, PVFF was the most important factor. In the fashion business, machine learning (ML) is mostly utilized for manufacturing and sales forecasting. Nevertheless, studies on the topic of clothing fit, which deters people from buying online, received little attention. This study experiments in the Python 3.11 platform to assess the proposed method's efficiency in terms of precision are 91.56%, recall is 0.89, f1-score is 0.91, accuracy is 93.99% and AUROC is 0.949 and area under the receiver operating characteristic curve (AUROC) are the performance metrics. By comparing the proposed and existing methods, the proposed method obtains superior performance. Thus, we proposed an innovative ML approach in this work to forecast customers' fulfilment with clothing fit. This study shows how the AI model works to increase customer happiness, decrease returns, and improve the entire online shopping experience for both customers and clothes merchants through extensive testing and validation.

Povzetek: Opisan je izvirni model umetne inteligence za oceno zadovoljstva kupcev s prileganjem oblačil. Uporablja metodo TSO-SLLR za napovedovanje prileganja oblačil, zmanjšuje vračila in izboljšuje spletno nakupovanje.

1 Introduction

The development of the internet and technology since its inception has fundamentally altered people's daily life has changed the world and its environment. This shift has formed a new norm for how consumers purchase products and services with impacted a wide range of sectors and industries, especially brick-and-mortar businesses [1]. In addition, social media usage has increased as a result of the advancement of internet technology and it's recognized as a vital component of society's daily existence. It's required of consumers in this age of online shopping to actively compare product information and share their knowledge by writing online reviews since an increasing number of goods and services are being provided online [2]. The fashion retail industry is in a phase of unparalleled transformation. For the foreseeable future, this is expected to pick up speed as well-established factors that are challenging the old model persist, such as an increase in internet buying and the consequent need for fewer physical establishments, automation and its effects on the workforce, fragmenting the competition and shifting customer behavior [3]. Additionally, clothes might expose a buyer to peer ridicule, which makes it connected with a larger social risk. For this reason, clothing purchases are heavily influenced by social and symbolic meanings [4]. Online clothing sales and purchases become increasingly challenging as a result, and fashion is the most popular category for purchases conducted Internet [5]. This study introduces a unique AI model that seeks to accurately evaluate the degree of purchasers' satisfaction with the fit of apparel (BF-CF). A unique machine learning algorithm called TSO-SSVM is used to predict BF-CF.

This is the structure of the remaining portion of the paper. The related work is provided in section 2. The TSO-SLLR approach is described in section 3. The study's findings are reported in section 4 and section 5 contains the conclusion.

2 Related works

The consumer experiences with AI chatbots, their applications and satisfactions, and the effect that consumer perceptions of AI-based customer support quality on satisfied consumers, brand loyalty, and repeat business [6]. To elucidate the relationship between various AI/ML tools and functions at the various stages of the Awareness, Interest, Desire, and Action (AIDA) model. This helped the merchants to identify possibilities and boost consumer confidence [7]. The present research was used to moderate the impact of service quality facilitated by AI on flow dimensions and the sensation of wonder experienced by consumers that combines the broaden-and-build theory with the flow dimensions [8]. To investigate at how online customers' astonishment and buying intention were affected by motivated consumers' inventive usage of digital voice assistants, a new conceptual framework centered on the broaden and built general, the stimulus organism response model and the consumer innovativeness notion was provided [9]. To comprehend the links between these factors and online clothing impulsive buying, looked at 10 online product presentation techniques and three customer characteristics in the current study [10]. Consumers of fashion were increasingly using virtual try-on (VTO) applications, although VTOs in the clothing sector have encountered opposition [11]. Investigating how consumers participate in omni-channel retail environments and take advantage of their benefits. In the context of Danang's fashion retailing industry, this article evaluated and validated the determinants of omni-channel buying intention using empirical research based on consumer analysis [12].To characterize the attention, cognitive, and emotional reactions, to the website of a fashion company and the behavioral consequences of online shopping reference[13] offered a comprehensive analysis. Customer satisfaction and repurchase intention were influenced by post-purchase online customer experience (OCX) [14] aspects of online garment retailing. By utilizing the Hedonic Information Systems Acceptance Model (HISAM) to identify the pragmatic and visual elements impacting customers' inclination to utilize intelligent apparel, the present study closes this knowledge gap [15]. The suggested connections were verified by bootstrapping, Hierarchical regression analytics (HRA), and covariance-based structural equation modeling (CB-SEM) [16]. To account for the imprecise opinions of specialists on the effects of different supply chain hazards, the Fuzzy analytic hierarchy process (FAHP) was employed. Using fuzzy numbers to represent the experts' opinions, the likelihood of different dangers was estimated [17]. To ascertain the primary determinants that impact the decisions of Iraqi adolescent females to acquire necessities over the Internet in Sulaymaniyah [18]. To elucidate the process via which the display of information affected consumers' behavioral responses and cognitive assessments, coupled with the significance of individual variations in the need for touch (NFT) [19]. Table 1 represents the related work summary table.

Table 1: Summary table for related work

Reference	Key findings	Results	SOTA lacks	Justification for the proposed study
[9]	The investigation found that consumer innovativeness had a favorable impact on buy intention and awe experience in online fashion purchasing, with awe experience mediating the relationship and electronic word-of-mouth mediating the relationship.	The structural equation modeling of data from 538 users indicates substantial correlations between variables.	The study lacks a comprehensive understanding of consumer motivations for AI-based voice assistants in fashion shopping, particularly how awe experience and electronic word-of-mouth influence purchase intentions.	The study integrates consumer innovation, AI voice assistants, and fashion shopping, offering insights for optimizing voice assistant services in online fashion retail.

[10]	Perceived hedonic and symbolic qualities of garments impact impulsive clothing purchasing inclinations, which in turn predict online clothing impulse buying. Certain product presentation approaches have a direct and moderating effect on these interactions.	Impulsive shopping tendencies are influenced by perceived hedonic and symbolic values, significantly predicting online apparel purchases. Product presentation methods also directly influence impulse buying.	The research frequently focuses on specific variables such as consumer traits or product presentations in isolation, rather than thoroughly investigating their interacting impact on online impulsive purchase behavior in the context of clothes.	The study explores the impact of various consumer characteristics and product presentation methods on impulse buying, addressing gaps in understanding online presentation methods' influence on clothes buying. It also provides insights into moderation effects, enhancing predictive models of online consumer behavior.
[14]	The study investigates post-purchase OCX aspects in garment commerce, emphasizing their influence on consumer satisfaction and repurchase intent.	Confirmatory factor analysis and structural equation modeling confirm the presented framework by supporting hypotheses about OCX, customer happiness, and repurchase intention.	Existing research lacks a thorough examination of post-purchase OCX dimensions unique to online clothes selling and their direct influence on the retention of customers.	The study encompasses knowledge gaps regarding comprehending how important post-purchase interactions impact buyer satisfaction and retention in online clothes shopping.
[16]	The study found that investing in the order fulfillment landscape in e-commerce environments had a bigger impact on customer buying intentions for fashion clothes than product selection. It emphasizes the role of fulfillment dependability as a moderator in improving shopping assistance for online buying scenarios.	CB-SEM, HRA, and bootstrap processes all confirm hypothesized connections. Shopping assistance and efficiency have been shown to have significant mediation impacts on e-tail servicescape characteristics and purchase intention. Fulfillment dependability has been discovered to modulate the association among e-tail servicescape characteristics and shopping assistance.	The research lacks a comprehensive exploration of fulfillment reliability's impact on e-tail servicescape dimensions and shopping assistance in online fashion retail contexts, and there is also a lack of comprehensive mediation analyses.	The study validates the mediate roles of shopping assistance and effectiveness and explores the moderate effect of fulfillment dependability, thereby leading to a better knowledge of how e-tail servicescape dimensions influence consumer behaviors and aiding in the development of more effective strategies for online fashion retailers.

[17]	Various dangers in green apparel supply chains in South and Southeast Asia have been classified into 5 major classifications and 18 particular risks. A significant influence was recognized in the financial and business environmental dangers.	FAHP was used to evaluate risk perception and possibility, emphasizing high occurrence possibilities for supply, demand, and process-related risks.	Existing research lacks extensive investigations which integrate fuzzy logic with the Analytic Hierarchy Process (AHP), particularly in the context of green clothes supply chains in South and Southeast Asia.	The proposed investigation fills this gap by offering a vulnerability matrix depending on effect and possibility, which could be useful in the establishment of resilient supply-chain approaches within the region.
[18]	Factors impacting online buying among young females in Sulaymaniyah, Iraq, which is the unavailability of products at local stores and dependence on online product evaluations.	The majority of participants, despite being unemployed, engage in purchases online at least once a month.	There has been limited study on online buying behavior among Generation Z girls in Iraq's Kurdistan Region.	Addressing a gap in the research by concentrating on a particular population (Generation Z females) in a distinct geographic setting (Sulaymaniyah, Iraq).

3 Material And methods

The purpose of this research is to assess customers' satisfaction with apparel that is acceptable for purchasing in the fashion industry. This involves corresponding with vendors, selecting the right product, and then performing the purchase so that it's sold in stores. A fashion buyer selects all of the clothing and accessories that are offered for sale to consumers, as shown in Figure 1.

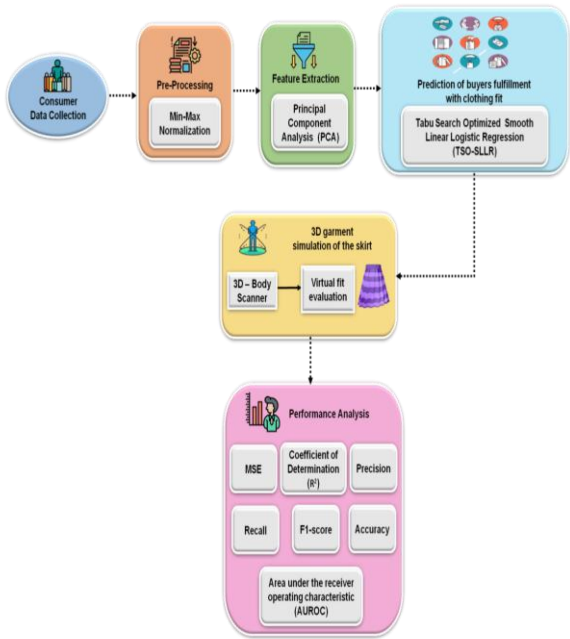


Figure 1: Overview of the proposed model

3.1 Participants

The target population for this study was consumers who frequently buy online, therefore female participants between the ages of 20 and 45 were chosen based on their high rate of online shopping. Considering that the study clothing size is experienced, participants with waist girths of 26–30 inches and hip girths of 36–40 inches were sought to find.

3.2 Pre-processing using Min-max normalization

Min-max normalization also referred to as deviation normalizing, constitutes a linear modification of the original data, where max represents the maximal and min represents the minimal of the sample's data. Using the counterfactual identification technique, the normal characteristic value is zero, and that of an irregular characteristic represents a positive integer. Therefore, it must be normalized to correspond to a natural integer. Data normalization is an essential phase in which every value has been expanded to the proper range. This approach facilitates in the elimination of massive deviations in characteristics.

$$\Psi_{ji} = Round\ [\left(\frac{Z_{ji}-min(Z_i)}{max(Z_i)-min(Z_i)}\right) * M] \qquad (1)$$

In equation (1), where Ψ_{ji} denotes the normalized value of Z_{ji} with a range of $0\ to\ M$ in integer form, $min(Z_i)$ is the minimal value of the i^{th} characteristic, and $max(Z_i)$ represents the maximal value of the i^{th} characteristic.

Min-max normalization scales data towards a 0-1 range, which improves the unique AI model's performance by increasing convergence speed, accuracy, and consistency when assessing consumers' satisfaction with clothing fit.

3.3 Feature extraction using PCA

PCA is considered one of the most frequently employed techniques for reducing data dimensionality. The primary objective is to organize the sample data from a space with higher dimensions towards a space with lower dimensions utilizing the orthogonal matrices. The $\boldsymbol{I_{PCA}}$ objective function is properly expressed as Equation (2):

$$\boldsymbol{I_{PCA}(Z) = \underset{O}{max} \sum_{j=1}^{m} ||z_j - \bar{z}||^2}$$
$$\boldsymbol{t.s. O^S o = J} \quad (2)$$

Equation (2) could be reduced to the subsequent tracing form following a simple algebraic change, such as equation (3).

$$I_{PCA}(O) = \underset{O}{max} \sum_{j=1}^{m} ||O^S(w_j - \bar{w})||^2$$
$$= \underset{O}{max}\, sq\{O^S (w_j - \bar{w})(w_j - \bar{w})^S O\}$$
$$= \underset{O}{max}\, sq\,\{O^S DO\}$$
$$t.s. O^S O = J \quad (3)$$

The covariance matrix is represented as $D = \sum_{j=1}^{m}(w_j - \bar{w})\,(w_j - \bar{w})^S$. $\bar{w} = \frac{1}{m}\sum_{j=1}^{m} w_j$, and $sq(*)$ represents the trace of $matrix *$, specifically the total of the main diagonal elements of $matrix *$.

PCA extracts important characteristics, reduces dimensionality, improves the AI model's efficacy, improves buyer fit forecasts, resulting in improved fulfillment assessments, individualized recommendations, and enhanced satisfaction, and improves the handling of inventory.

3.4 Test clothes

The sample skirt measurement is eighteen inches in length and twenty-nine inches across the waist. All test skirts were made with the same form and color (black), among other design elements, and alternate materials with distinct mechanical characteristics were employed since fabric attributes were selected to serve as variables of input for estimating the participants' BF-CF. Because knitted fibers are frequently appropriate for tight clothing, woven fabrics were chosen. In light of this, fabric providers supplied a variety of woven textiles in black, each with a unique composition and structure.

3.5 Measurements of the fabric

The prediction model in this study was developed using the following mechanical properties of fabrics: weight (W), thickness (T), friction coefficient (F) on the face and rear of a cloth, bending rigidity (B), thickness (T), surface roughness (R) along the weft and warp directions of the fabric, and extension (E). Following fabric property measurements, four groups were formed out of the seven skirts. It's necessary to group for two reasons: (1) each participant would need to spend nearly half a day evaluating all seven skirts, which could be exhausting and confusing and (2) there was a tiny difference in several fabric qualities, giving the impression that the skirt simulations were similar to one another. Participants were able to try on skirts from different groups more easily and rapidly as a consequence of the textiles that were sorted into categories.

3.6 Virtual and physical try-on of clothing

Each participant received an invitation to the study area to participate in the fitness evaluations. Utilizing a 3D body scanner, each person is scanned while wearing clothing. The scan surfaces were retained as STereoLithography (STL) (binary) files after being rebuilt in ScanWorks with the standard posture option. The GeoMagic Wrap application was used to resize, smooth, and save these files. Participants completed a few more Qualtrics questions once their 3D bodies were scanned. A flatbed scanner is used to scan and convert the fabric textures utilized in the skirt simulations. The cloth editor window in the clothing simulation program was then updated with virtual fabric attributes. To provide the virtual textile texture, Product design specification (PDS) is utilized to open the scanned cloth images, it's hard to determine between the different fabric textures. Since fit is the primary consideration during the virtual try-on, the texture images of every test cloth were left as-is in the program.

3.6.1 Participant measurements and levels of body satisfaction

The 3D body scans were used to obtain nine body measures that would affect how well skirts fit. The Body Satisfaction Scale, a 7-point Likert-type measure, was used to gauge participant's body satisfaction concerning 22 items. Because only sixteen of the criteria were significant in predicting skirt fit satisfaction, only sixteen were selected. The individuals' BF-CF are predicted using internal parameters as variables. Fabric characteristics were one of the other predictor factors employed in this investigation. To mitigate the absence of tactile perception in virtual clothing by employing the techniques outlined, the materials' mechanical characteristics must correspond with the test fabrics' tactile characteristics.

3.7 Prediction of buyers' fulfilment with clothing fit using Tabu search optimized smooth linear logistic regression (TSO-SLLR)

To improve prediction accuracy in the fashion retail industry, Tabu Search Optimized Smooth Linear Logistic Regression (TSO-SLLR) is a technique that predicts purchasers' fulfillment with apparel fit for smoother decision boundaries.

3.7.1 Tabu Search Optimization (TSO)

The customers' satisfaction assessment of a meta-heuristic optimization algorithm known as tabu search is to find buyers for issues that are difficult to address using traditional optimization techniques. By making adjustments to the existing that address to prevent repeating the same modification, the approach progressively improves a forecast of a problem. It is achieved by recording tabu movements and changes that are forbidden from being performed during the current search.

The buyer's response is repeatedly refined using the Tabu search approach, which is based on the buyer's original solution to the issue. The cloth fit selects an improvement that can be chosen at each stage after examining the possible alternatives to the current response. A Tabu move with a lower probability might be performed by the algorithm if no moves of this kind could be located. The method continues to run the pending as it reaches a preset finish point, the highest quality iterations possible.

3.7.2 Smooth linear logistic regression (SLLR)

A regression methodology called SLLR has employed predictions about a dependent variable using two groups. There are several categories for the dependent variable based on a coding system where a zero or a one indicates the presence or absence of an event. The goal of SLLR is to identify the best model for describing the connection between a set of independent factors and a dependent variable with two categories. This gives rise to the following expression for the logistic function described in Equation (4) with p number of variables that are independent.

$$P(Z=1)=\frac{1}{1+e^{-(\beta_0+\beta_1 y_1+\beta_2 y_2+\cdots\ldots\beta_p y_p)}}=\frac{e^{(\beta_0+\beta_1 y_1+\beta_2 y_2+\cdots\ldots\beta_p y_p)}}{1+e^{(\beta_0+\beta_1 y_1+\beta_2 y_2+\cdots\ldots\beta_p y_p)}} \quad (4)$$

Where the probability of the pertinent occurrence involving a dependent variable is represented by statement $P(Z=1)$, and the regression coefficients are represented by statement $\beta_0, \beta_1, \ldots, \beta_p$. Should the likelihood of the pertinent event occurring be a dependent factor, then the result variables having a range of values from 0 to 1. Additionally, a linear model is produced via logistic regression, which is the ordinary logarithm of the rate of $C(X=1)$to $1-C(X=1)$ in the model:

$$g\ (x)=ln\left(\frac{C(X=1)}{1-C(X=1)}\right)=\beta_0+\beta_1 y_1+,\ldots.,\beta_p y_p \quad (5)$$

$g\ (x)$ in equation (5) has several characteristics that are ideal for a SLLR model. In this case, the variables that are independent are combined with continuous and categorical variables and incorporated into the model. The study utilizes the greatest probability prediction to forecast the $\beta_0, \beta_1, \ldots., \beta_p$ parameters once a logit variable is created from the dependent variable. This method integrates the adaptability and predictive capacity of SLLR models with the advantages of TSO approaches. Through the integration of these techniques, TSO-SLLR seeks to improve buyer fulfillment prediction accuracy and efficiency, allowing businesses to make data-driven decisions that maximize customer pleasure and propel success in competitive marketplaces. The following algorithm 1 represents the generic Tabu Search algorithm formulation.

Algorithm 1: Tabu Search algorithm smooth linear logistic regression (TSO-SLLR)

Step 1: Initialize solution **consumer cloth fit satisfaction** starts from a route that begins at the "start" node and repeatedly links to the next closest node to it before returning to the "start" node.
Step 2: Initialize the Tabu and regression List is empty
Step 3: While there is a violation of the halting condition:
Generate a series of feasible paths by slightly altering the existing path.
Determine the distance traveled by analyzing each possible route.
Select the most efficient route that doesn't show the Tabu List with the least amount of travel.
Step 4: Update the current route is added to the Tabu List
Step 5: IF return to a loop as the halting requirement has not been satisfied.
Step 6: IF the current set of routes is the best option, the halting conditions are satisfied.

4 Performance analysis

In this paper, Python 3.11 is used to evaluate the Tabu search optimized smooth linear logistic regression (TSO-SLLR). The existing methods are contrasted with the TSO-SLLR algorithm, including the k-means-Artificial Neural Network (k-Means-ANN) [20], and adaptive genetic algorithm (GA) + K-means-ANN (adaptive GA+K-means-ANN) [20]. The parameters include MSE, and coefficient of determination (R^2). Table 2 shows the outcomes of proposed and existing methods.

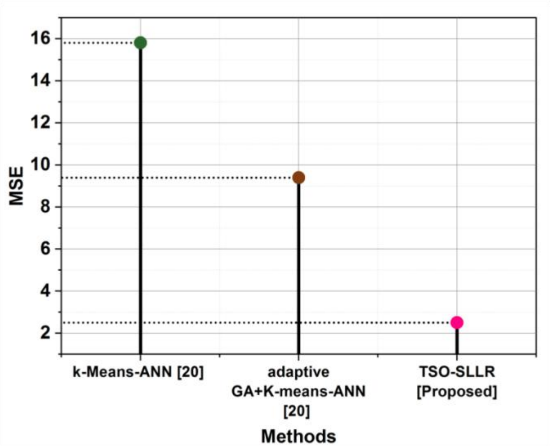
Table 2: Numerical outcomes of the suggested and existing techniques

Methods	MSE	Coefficient of Determination (R^2)
k-Means-ANN [20]	15.8	82.38
adaptive GA+K-means-ANN [20]	9.4	98.6
TSO-SLLR [Proposed]	2.5	99.63

Mean square error (MSE) by dividing the total number of values of a variable by the squared difference between its observed and predicted values. The results of the MSE for both proposed and existing techniques are shown in Figure 2. The results are compared with those of existing approaches and the MSE of TSO-SLLR is determined such as the k-Means-ANN (15.8), adaptive GA+K-means-ANN (9.4), and TSO-SLLR has (2.5) in terms of MSE. The suggested TSO-SLLR approach outperforms other methods in terms of efficiency.

To forecast the result of a specific event, a statistical measurement called the coefficient of determination looks at how differences in one variable are explained by variations in another. A comparison of the coefficient determination for the suggested and existing methods is shown in Figure 3. The suggested approach TSO-SLLRobtains (99.63), adaptive GA+K-means-ANN (98.6), and k-Means-ANN (82.38), respectively.

Figure 2: Comparison of MSE



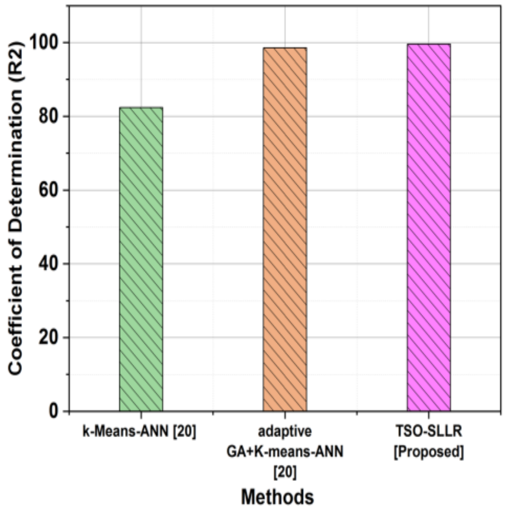


Figure 3: Comparison of Coefficient of Determination

4.1 Participant preferences and demographics

Table 3: Participant's satisfaction levels

Body Part	Sample category (n=57)	
	Mean Satisfaction	Standard Deviation (SD)
Height	5.6	1.3
buttocks	5.1	1.8
Ankles	5.4	1.5
Feet	5.3	1.4
Knees	5.2	1.3
Thighs	4.28	1.7
Abdomen	4.31	1.3
Hips	4.34	1.4
Weight	4.34	1.6

The experiment participants were fifty-seven females. To gain insight into the participants' general satisfaction with the way market-ready skirts fit them and their favorite styles of skirts, as added two more questions to the evaluation: one focused on the style preferences of participants, while the other examined the fit of casual clothing skirts available in the market. However, a participant's assessment of fit would be impacted by how they felt about a certain style. Thus, we surveyed to find out whether participants thought circular skirts were a fashionable trend. In the meanwhile, tests were conducted on other skirt designs. Table 3 demonstrates that participants' satisfaction levels were lowest in the mid-body and highest in the lower body.

The use of a circular skirt as the test sample was validated using pre-tests as the findings indicated the similarity ratings of the other types of skirts did not exhibit any statistically significant variation. Based on their similarity ratings, only two individuals expressed varying degrees of hatred towards the circle skirt design, with three individuals were unable to share any opinion on the style. Table 4 shows the characteristic levels of participants.

Table 4: Characteristic levels of participants

Characteristic	Minimum	Maximum	Mean	Standard Deviation (SD)
Weight (lbs)	105	154	130.7	12.7
Height (inches)	60	70	65	2.5
BMI	18.6	24.9	22	2
Waist Girth (inches)	24.5	30.1	28	1.6
Hip Girth (inches)	34	44	38.2	2

4.2 Examination of fabric characteristics and categorization

The textiles are grouped and their measured qualities are displayed in Table 5 skilled seamstress finished preparing seven clothes. These seven textiles ranged in thickness from 0.11 to 1.28 mm and weight from 123 to 386 g/m2. Their shear rigidities (19.11–232.27 N/m) and bending rigidities (0.95–20.47 μNm) differed significantly in the warp direction. The drape of the textiles was notably different, as these data verified, and this resulted in participants' various aesthetic fit assessments are described in detail in the following paragraphs.

Table 5: Measured fabric properties and groupings identified

Group	Fabric code	Composition	Thickness (mm)	Weight (g/m^2)	Elongation (%) (under 500 gf)		Shear rigidity (N/m)	Bending rigidity (μNm)		Surface roughness (μm)	Surface friction (no unit)	
					Weft	Warp		Weft	Warp	Face	Back	Face
1	Cloth 1	100 percentage Cotton	0.11	123	11.42	4.35	44.21	0.59	1.08	12.07	0.72	0.64
	Cloth 2	100 percentage Wool	0.22	145	14.15	14.22	19.11	0.95	0.91	13.77	0.64	0.71
2	Cloth 3	98/2 percentage Co/EA	0.32	236	15.44	2.08	207.50	2.69	7.62	14.39	0.88	0.94
	Cloth 4	68/28/4 percentage Co/PES/EA	0.45	259	21.02	3.15	122.67	3.98	7.32	17.09	0.65	0.91
3	Cloth 5	96/4bv percentage Co/EA	0.66	338	25.03	2.64	232.27	6.81	24.14	11.37	0.91	1.05

	Cloth 6	96/4 percentage Co/EA	0.63	386	27.04	3.56	143.21	7.62	16.72	12.78	0.71	0.92
4	Cloth 7	100 percentage Wool	1.28	345	5.36	3.88	122.92	2.93	9.42	20.47	0.94	2.00

Table 6: Participants' average BF-CF and PVFF

Categorize	Code for skirts	BF-CF		PVFF	
		SD	Mean	SD	Mean
1	Skirt 1	1.13	6.34	1.10	5.46
	Skirt 2	1.16	6.25	1.05	4.86
2	Skirt 3	1.24	4.59	1.23	4.76
	Skirt 4	1.18	5.15	1.19	4.84
3	Skirt 5	1.52	5.79	1.18	5.79
	Skirt 6	1.17	4.98	0.92	5.68
4	Skirt 7	1.19	6.07	1.9	5.68

Test skirts were numbered based on the fabric codes were made of for pragmatic purposes. Each participant received roughly the same amount of actual and virtual tryons for each skirt. The BF-CF and PVFF of each participant for each skirt were computed. The average fit satisfaction of the participants was calculated to have an improved idea of which skirts had the greatest fit satisfaction rate, as shown in Table 6. The fit of Skirts 1, 2, and 4 was rated as the most satisfactory by participants, whereas Skirt 6 received the lowest satisfaction rating based on BF-CF information that is attributed to the materials with bending rigidities, which were closely linked to the way fabrics draped. Higher bending rigidity cloths were stiffer and didn't fold in a visually appealing way.

4.3 Comparative analysis

In the comparative analysis, precision, recall, f1-score, area under the receiver operating characteristic curve (AUROC), and accuracy are the performance metrics we utilized. The existing methods are random forest (RF), decision tree (DT), and extreme gradient boosting (XGB) [21]. Table 7 represents the numerical outcomes of existing and proposed methods.

Table 7: Numerical outcomes of existing and proposed methods

Methods	Precision (%)	Recall	F1-Score	Accuracy (%)	AUROC
RF [21]	89.93	0.74	0.9007	90.51	0.932
DT [21]	89.9	0.75	0.8998	90.54	0.922
XGB [21]	89.14	0.76	0.8905	89.94	0.937
TSO-SLLR [Proposed]	91.56	0.89	0.91	93.99	0.949

4.3.1 Precision

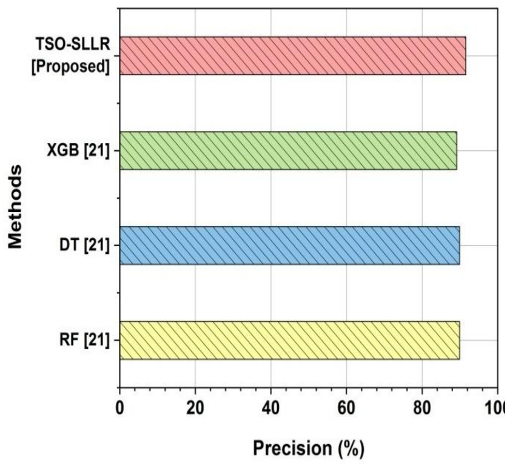


Figure 4: Graphical outcomes for precision

Precision for an AI model assessing consumers' satisfaction with clothes fit estimates the proportion of accurately recognized suitable fits among every fit established to be adequate by the model. Figure 4 shows the precision results of the proposed and existing methods. RF (89.93%), DT (89.9%), and XGB (89.14%) are the existing numerical outcomes for precision. When comparing the outcomes of the existing method, the TSO-SLLR method obtained 91.56% better precision.

4.3.2 Recall

Recall estimates the proportion of real positive instances (satisfied consumers) properly recognized using the AI model evaluating apparel fit satisfaction, which is essential for understanding buyer satisfaction and generating better recommendations. Figure 5 shows the recall outcomes of proposed and existing methods. RF (0.74), DT (0.75), and XGB (0.76) are the existing numerical outcomes for recall. The TSO-SLLR method attains with a score of 0.89 which provides better recall when comparing the outcomes of the existing method.

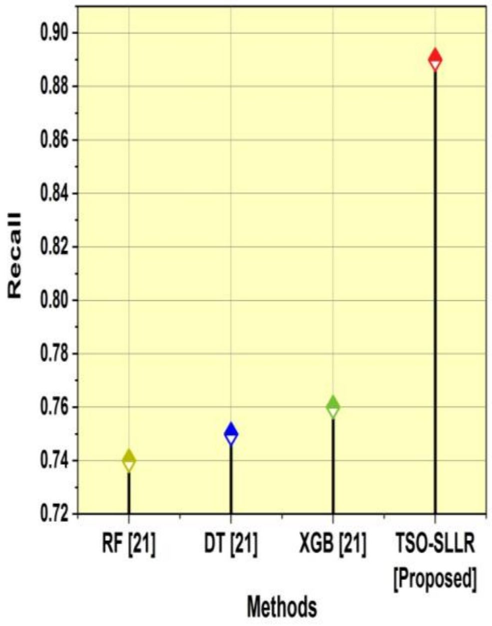


Figure 5: Graphical outcomes for recall

4.3.3 F1-score

The F1-score balances precision and recall, which is essential for examining AI models that predict clothing fit satisfaction. This considers false positives and negatives, offering a complete assessment of the model's performance. Figure 6 shows the F1-score results of the proposed and existing methods. RF (0.9007), DT (0.8998), and XGB (0.8905) are the existing numerical outcomes for precision. When comparing the outcomes of the existing method, the TSO-SLLR method obtained a 0.91 score with better precision.

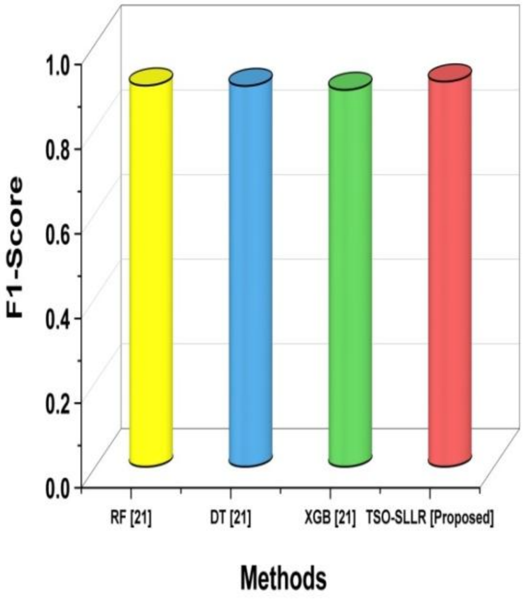


Figure 6: Graphical outcomes for F1-score

4.3.4 Accuacy

Accuracy for an AI model measuring customers' clothes fit fulfillment assesses how accurately the model forecasts buyer satisfaction with apparel sizes and fit, hence improving the whole shopping experience and lowering returns. Figure 7 shows the accuracy outcomes of proposed and existing methods. RF (90.51%), DT (90.54%), and XGB (89.94%) are the existing numerical outcomes for accuracy. The TSO-SLLR method attains with a score of 93.99% which provides superior accuracy when comparing the outcomes of the existing method.

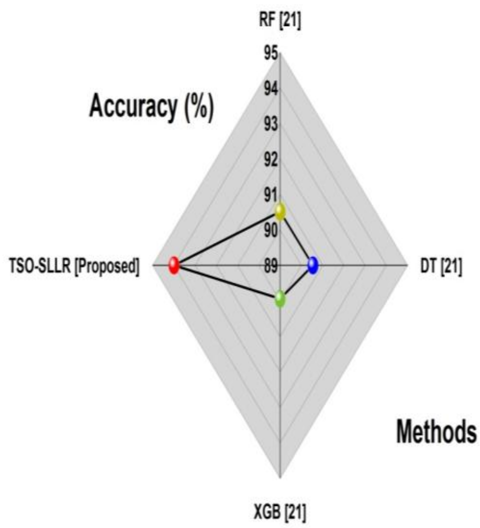


Figure 7: Graphical outcomes for accuracy

4.3.5 Area under the receiver operating characteristic curve (AUROC)

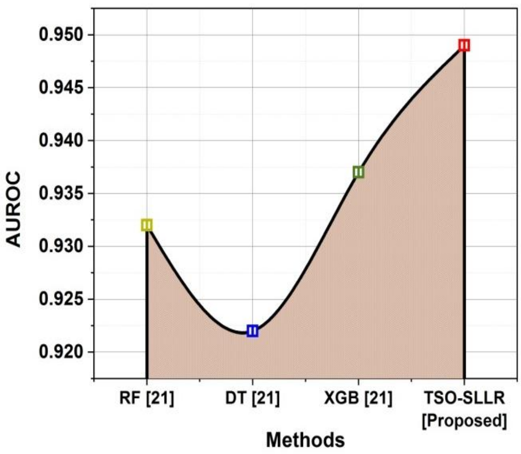


Figure 8: Graphical outcomes for AUROC

AUROC assesses the AI model's capacity to discriminate between satisfied and dissatisfied consumers depending on clothing fit, calculating its discriminating power in terms of true positive and false positive rates. Figure 8 shows the AUROC outcomes of proposed and existing methods. RF (0.932), DT (0.922), and XGB (0.937) are the existing numerical outcomes for AUROC. When comparing the outcomes of the existing method, the TSO-SLLR method achieves (with a score of 0.949) superior AUROC results.

5 Discussion

The constraints of k-Means-ANN [20] are sensitivity to initial centroids as well as constant cluster numbers, and localized minima within nonlinear information distribution. Massive computational resources, sophisticated parameter adjustment, and being susceptibility to premature convergence could be required are the limitations for adaptive GA+K-means-ANN [20]. Complex datasets are prone to excessive fitting and are sensitive to smaller alterations, which leads to instabilities are the restrictions for RF [21]. The limitations of DT [21] are training time with massive data sets is slower and poorer interpretability than individual decision trees. Susceptible to excessive fitting whether the hyper-parameters aren't correctly tuned, and that can be computationally costly are the constraints of XGB [21]. Through analyzing the drawbacks of the existing methods, our TSO-SLLR method provides better performance.

6 Conclusion

The research recommended the procedure for an ML approach utilized for evaluating buyers' fulfilment with clothing fit is utilized as a TSO-SLLR. Virtual try-on technology is still not widely adopted by businesses and customers, despite several attempts to use it for online shopping. Creating a realistic body model of the customer has proven to be one of the biggest challenges in the use of virtual try-ons for online shopping. The development of digital clothing and fabric libraries is another significant challenge. Fashion businesses are generating these libraries more quickly as they start to focus more on 3D design and change the way they produce new products. The suggested TSO-SLLR approach in digital clothing simulations is effective in lessening issues with garment fit that arise from online clothing purchases. The suggested approach outperforms evaluating buyers' fulfilment with clothing fit prediction models MSE (2.5), and coefficient of determination (99.63). The proposed TSO-SLLR method outcomes of precision are 91.56%, recall is 0.89, f1-score is 0.91, accuracy is 93.99% and AUROC is 0.949. In this research, the TSO-SLLR method provides superior performance. In the event that fashion tastes change rapidly, limited sellers that purchase apparel in large quantities run the danger of having obsolete inventory. The TSO-SLLR approach has the potential to transform online shopping by properly forecasting buyers' satisfaction with apparel fit, lowering the rate of returns, and improving customer experience. An ethical consideration that includes reducing prejudices and promoting diversity in fashion shopping, models must respect varied body proportions and cultural perspectives of fit. In the future, as virtual try-one becomes an essential component of online shopping, fashion companies may find that the techniques outlined in the study help them decrease return rates, enhance customer satisfaction, and make their digital samples more realistic rather than image-shopped for advertisements.

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