Customized Car Seat Design with GAN-Based Generative Models and Random Forests for Comfort Evaluation

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An automobile seat is an essential part that reduces vibration in addition to provide comfort and restraint to its passenger. Automotive seat designs place a high value on dynamic comfort since the seat is in continuous touch with the passenger of the vehicle. Personalized comfort and ergonomic adjustability are becoming crucial differentiators in contemporary automobile design. In order to optimize automobile seat design utilizing 3D printing technology, this research suggests an intelligent framework that blends Random Forests (RF) and Generative Adversarial Networks (GAN) using python. Data were preprocessed using min-max normalization and then reduced using PCA for feature extraction. GAN created unique seat designs, while RF classified and adjusted comfort levels. The GAN-RF method performs better, according to quantitative data, with 97.5% precision, 97.8%recall, 98.0% accuracy and an F1-score of 97.6% in comfort prediction. The framework integrates anthropometric data collection, computational ergonomics, and additive manufacturing to achieve user-specific seat geometries and material distributions. By employing multi-objective optimization, vibration absorption, pressure distribution, and long-duration comfort are simultaneously enhanced. Prototypes fabricated using 3D-printed lattice and gradient structures demonstrate superior adaptability compared to conventional foam-based seats. The proposed approach not only improves passenger well-being and reduces fatigue during extended driving but also establishes a pathway toward sustainable, on-demand, and modular seat production in the automotive industry.

Povzetek: Študija predlaga inteligentno metodo za personalizirane avtomobilske sedeže, ki z GAN-i generira zasnove, z naključnim gozdom prilagaja udobje ter z večciljno optimizacijo in 3D-tiskanimi strukturami izboljša dušenje vibracij in porazdelitev pritiska.

1 Introduction

Facing intense global competition, automakers are increasingly designing vehicles that prioritize customer satisfaction and preferences. The attitude of drivers, among other needs, is therefore an important factor that should be appropriately and precisely considered in the design and development of automobile seats [1]. Digital manufacturing, artificial intelligence, and human-friendly design innovations have transformed the automobile industry in many ways over the last few years. One area of innovation - customizing and optimizing automobile seats for comfort - is particularly crucial with respect to the safety, comfort, and overall experience of drivers and passengers. Car seat design is being transferred from standardized, mass-producing products to higher level, customized systems designed to effectively serve the requirements of each individual, as modern-day customers want the degree of safety and utility but also personalized comfort [2]. The comfort and safety of the operator (driver) of the vehicle is important to prevent accidents and injuries on the roadway. Having a safe and comfortable driver's seat is very important when designing and constructing an automobile. There are no options for customizing vehicle seat ergonomics, even though the market's desire for innovation has made customized items a top priority [3]. This is true even if there are many ways to customize the trim, seat coverings, and in-seat comfort amenities. The hardness of the seat cushion cannot be changed, despite these choices and research demonstrating the advantages of modified seat pressure distribution [4]. This may be explained by extremely efficient Just-In-Time (JIT) assembly procedures, where every new element that has to be modified requires a lot of work and, thus, extra expenses. However, the expensive sports and luxury automobile market does not provide such choices, even if car seats in this market are still created by hand in tiny amounts [5]. Furthermore, these vehicles are advertised for a single person, who may be a sporty driver or a comfortable passenger.

Large-format 3D printing was essential to making this concept design a reality, and the automobile industry is now using the technology to test new design concepts and provide creative solutions to the market, from quick prototypes to final components. Numerous initiatives have made use of the technology's capacity to produce intricate designs that are optimized for comfort and performance, as well as mass-produced customized goods, particularly in the automobile seats industry. The industry's drive towards more automation has coincided with a rise in the anticipation of the arrival of completely autonomous automobiles. Mobility and the transport sector will need a significant development in the future when such technologies become available in the general industry [6]. However, the hunt for new use cases has increased as a result of mobility optimization via more effective use of travel time, and they need to be examined. Driving is no longer a primary activity in autonomous driven systems [7], and travel may serve new secondary functions. The driver and the driving duties, places, and instruments are now the main emphasis of the car's interior design. There are additional uses for this same area than driving. Car makers are spearheading a rigorous and daring research to find new vehicle ideas, which includes developing models and designs to define the inside of future vehicles [8]. Concurrently, a number of surveys and studies have been conducted to ascertain the intended functions of automobile interiors. Sleeping or resting is one of the most sought-after vacation activities [9]. The cabin as it now exists must be significantly altered to permit sleep activities within the car.

The existing accessibility, ergonomic, and vehicle safety features were designed and implemented over a long period of time, with knowledge changing in tandem with societal demands and technological advancements. It is crucial to research, anticipate, and predict the new future circumstances in order to develop systems that can adjust to new use cases of high automation in the automotive industry. Prototypes must be made in a variety of ways, both physically and visually, in order to envision and test new interior spaces for the research of this future scenario. It is also necessary to build technological solutions for such notions. Both patents and scholarly articles that examine various technological solutions are included in the literature. However, because of the difficulty of creating such high-fidelity prototypes, the actual or nearly genuine physical experience of occupants is often not exploited. As a result, the majority of the information that has been established in this sector so far has come from the construction of hypothetical situations and very restricted user experiences. Additionally, user research and testing in the autonomous car domain have preconceived, incorrect views about the future's appearance and feel based on existing vehicles and expectations.

However, geometry customization alone is not enough to provide genuine personalization and comfort optimization. Machine learning (ML) algorithms evaluate user data (such as body form, posture, pressure distribution, and preference feedback) and provide optimized designs that optimize comfort and support throughout a range of driving scenarios. This necessitates a data-driven, intelligent design approach. Additionally, adaptive feedback loops for continually modifying seat characteristics are made possible by integration with smart sensors and real-time data collecting, such as from pressure sensors, accelerometers, and thermal imaging. Manufacturing-wise, the combination of 3D printing and AI-powered design optimization makes it easier to create seat systems that are lightweight, environmentally friendly, and energy-efficient.

In order to overcome this difficulty, the research provide a hybrid creative Adversarial Network–Random Forest (GAN–RF) approach that combines the predictive resilience of ensemble ML with the creative powers of deep learning to provide a complete car seat customization solution.

1.1 Research motivation

The motivation for this research is to enhance car seat design through artificial intelligence and 3D printing. Traditional methods lack personalization and adaptability to user-specific ergonomics. By integrating Generative Adversarial Networks (GAN) with Random Forest (RF) classifiers, this research enables customized, data-driven comfort optimization, ensuring improved ergonomics, reduced development time, and user satisfaction.

1.2 Contribution of this study

The study offers a novel AI-driven method for customized car seat design by combining GAN and RF to generate and classify customized seat configurations based on user-specific data.

- The research aims to enhance combining GAN-based generative models with Random Forest classification to create personalized car seat designs, integrating anthropometric data and comfort evaluations for adaptive, ergonomically optimized seating solutions.
- Research employed a comprehensive dataset with 1,800 records integrating anthropometric, biomechanical, and subjective comfort data.

- Data processing with min-max normalization and PCA enhances feature extraction, while GAN generates customized 3D-printed seat prototypes and RF classifies comfort levels using biomechanical features and user feedback.
- Designs were rapidly prototyped using 3D printing for validation and subjective evaluation.
- Research Suggested integration of reinforcement learning, adaptive materials, and real-time physiological monitoring for continuous seat optimization.

2 Literature review

Research developed and evaluated a somatosensory simulation control algorithm for animation VR sports to enhance realistic, responsive, and immersive motion experiences [10]. VR sports simulation dataset including indoor tennis, realistic somatosensory games, and various animation VR movements is utilized. Performance metrics include response time/feedback latency, phase delay consistency, motion prediction accuracy, and error reduction in angular velocity and acceleration. Algorithm effectively predicted terrain undulations and enhances the consistency of VR animation movements. Performance varies with extremely complex or irregular terrain and real-world validation limited to simulated experiments. The research evaluated a 7DOF biodynamic model to predict human response to low-frequency vehicle vibrations and optimize seat suspension comfort [11]. Simulation data include sinusoidal and random road excitations (classes A–E) at varying speeds, with seat/cushion stiffness, damping, and head acceleration are utilized. Driver's head acceleration, peak transmissibility ratio, and seat effective amplitude transmissibility for ride comfort evaluation. Reducing seat stiffness and damping, individually or together, lowers head acceleration, peak transmissibility, and SEAT, while adjusting cushion damping and stiffness enhances comfort. Real-world validation with human subjects is limited. Multi-occupant and dynamic seating configurations not analysed. Table 1 illustrates the relevant existing articles of the research.

Table 1: Summary on related works

Ref.	Objective	Dataset	Performance Metrics	Key Findings	Limitations
Akbari et al. [12]	Develop and benchmark machine learning models to predict mechanical properties in metal additive manufacturing, improving accuracy, interpretability, and cost-efficiency.	Dataset compiled from 90+ MAM articles and 140 data sheets, including processing parameters, machines, materials, and key mechanical properties.	Prediction accuracy (R^2, RMSE) Mean Absolute Error (MAE) Model interpretability via SHAP values	Physics-aware featurization enhances model accuracy, enabling ML models to reliably predict mechanical properties across diverse metal additive manufacturing processes.	Limitations include incomplete coverage of MAM materials and machines, with predictions dependent on the quality and completeness of source data..
Ahsan et al. [13]	To optimize transfer learning (TL) models for early defect detection in 3D-printed objects, improving AM product quality through image-based monitoring.	Images of 3D-printed objects from three different datasets, covering various defect types, geometries, and printing conditions, used for training and evaluating TL models.	Accuracy, precision, recall, F1-score, optimizer effectiveness (Adam, SGD, RMSprop), and model interpretability via LIME.	Adam and RMSprop optimizers enhance model performance, while EfficientNetB0, B7, and V2M perform poorly when using the SGD optimizer.	Real-time deployment and scalability not fully tested. High computational resources needed for large TL models.

Elrefaie et al. [14]	The research aims to develop DrivAerNet, a large-scale CFD dataset, and RegDGCNN, a dynamic graph CNN model, for fast, accurate aerodynamic car design.	DrivAerNet: 4000 high-fidelity 3D car meshes with ~0.5 million surface mesh faces each, including wheels and underbody, with aerodynamic data (3D pressure, velocity fields, wall-shear stresses).	Drag estimation accuracy (R^2, RMSE) Prediction time (seconds per 3D mesh)	Enables fast drag estimation in seconds. Facilitates rapid aerodynamic assessments and accelerates car design processes.	Model performance can vary for highly unconventional car geometries. Real-world validation with experimental wind tunnel data is limited.
Regenwetter et al. [15]	AutoML is used in this work to forecast bicycle frame structural performance indicators.	4,500 bicycle frames with simulated structural performance measures make up the dataset.	Decreased MAE by 12.5% and increased F1 score by 24% compared to conventional models.	When it comes to forecasting structural performance, auto ML performs better than standard.	Particular to bicycle frames; modification is necessary for car seat application.
Greif [16]	This work uses ML to forecast CO2 emissions in additive manufacturing processes.	Numerous datasets including CO2 emissions and AM process parameters	Model-specific RMSE and other error measures range from R2 to 0.9977.	Sustainable design is aided by ML models' ability to forecast environmental implications with accuracy.	focused on sustainability; there is no obvious link between this and comfort optimisation.
Naser et al. [17]	To develop a data-driven LCA (DD-LCA) framework integrating ML and product-process codesign to predict environmental impacts of additive manufacturing.	The dataset comprises 200 entries for the Fused Filament Fabrication (FFF) process, encompassing 5 design features, 7 process parameters, and 18 environmental impact categories.	Prediction accuracy (%) Root Mean Square Error (RMSE) Generalizability on unseen data Feature importance analysis.	XGBoost and MLP algorithms achieved high prediction accuracy (98%) with low RMSE (0.029).	Other additive manufacturing processes not analysed. Predictive accuracy can vary with untested feature combinations.
Diatezo et al. [18]	This document Use conductive inks to design and optimise 3D-printed heating textiles for automobile seats.	data from experiments on the electrical and thermal properties of printed coatings.	Response time, temperature uniformity, and heating efficiency.	Printed coatings provide easier integration, quicker heating, and energy efficiency.	Requires more knowledge of the properties of the material in order to be produced on a wide scale.

Jayasudha et al. [19]	To use a variety of ML techniques to forecast the tensile robust parts that are three-dimensional printed.	Experimental information on known-tensile-strength 3D-printed components.	Unspecified; models include decision trees, AdaBoost, and others.	Mechanical characteristics can be accurately predicted by ML models, which helps with design optimisation.	The application to seat comfort has to be investigated; specific performance indicators are not specified.
Banijamali et al. [20]	The author utilizes ML to predict the flexibility of 3D-printed structures based on sensors.	Information on electrical characteristics and the associated flexural strengths.	Unspecified; models consist of SVR, linear regression, and others.	Real-time monitoring is possible by ML models' ability to infer- mechanical characteristics from sensor data.	Strength training for young children is prioritised above comfort and long-term performance.
Qayyum et al. [21]	This research predicts the compressive characteristics of 3D-printed materials utilizing ML with small datasets.	Tensile specimens with different levels of reinforcement make up this small dataset.	Depending on the reinforcement content, prediction errors varied from 2 to 41%.	Rapid prototyping is facilitated by ML models' ability to anticipate attributes even with little data.	Higher reinforcement levels result in significant prediction mistakes; accuracy requires bigger datasets.

3 Methodology

To optimize automobile seat design utilizing 3D printing technology, this research suggests an intelligent framework that blends Random Forests (RF) and Generative Adversarial Networks (GAN). 3D Printed Car Seat Customization Dataset is gathered from kaggle. Data were preprocessed via min–max normalization and reduced using PCA for feature extraction. Generative Adversarial Networks (GAN) generated customized seat designs, while RF classified and optimized comfort levels. Designs were rapidly prototyped using 3D printing for validation and subjective evaluation. Figure 1 illustrates the methodological flow.

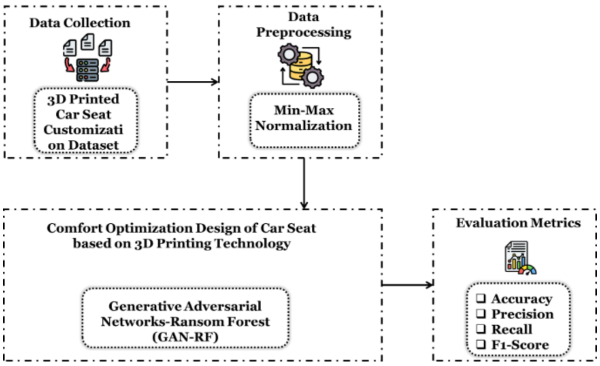

Figure 1: Illustration of the methodology flow

3.1 Dataset

The 3D Printed Car Seat Customization dataset [24] consists 1,800 rows and includes anthropometric data, user posture preferences, material/structural configurations, and comfort evaluation measures. Each record corresponds to a specific individual, complete with body dimensions, driving patterns, and seat comfort ratings. Features include height, weight, hip breadth, shoulder breadth, preferred posture, driving duration, material type, lattice density, and gradient structures. The dataset also includes goal comfort scores for pressure distribution, vibration absorption, long-term comfort, fatigue reduction, and overall satisfaction. For model development, the dataset was partitioned into 70% training, 30% testing using stratified sampling to preserve comfort level balance (low, medium, high).

(https://www.kaggle.com/datasets/programmer3/3d-printed-car-seat-customization-dataset)

3.2 Preprocessing using Min-max normalization

The variables are changed such that they all fall within a certain range in order to normalize seat comfort. Normalization is an important step in classification frameworks whether employing proximity metrics or computational models. By normalizing the input values for every measured attribute in the training set, the neural network propagation backward technique can speed the training phase of classification. Min-max normalization is a preprocessing technique that scales input features into a fixed range, typically 0 to 1, ensuring uniformity across variables. In this research, it enhances model stability, improves GAN–RF training efficiency, and ensures accurate, unbiased comfort classification for personalized car seat design. Making the original data linear is the goal of min-max normalization.

Consider that the minimum and maximum values for an attribute X are $minX$ and $maxX$. B value of B, a_x, is mapped to a_x in the range [new- $minx$, new- $maxX$] by using the following Equation 1.

$$\ddot{B}_y = (B_y - minx)/(max\, x - \min x) * (new_{maxx} - new_{minx}) + new_{minx} \quad (1)$$

The relationship among the initial values of a collection is maintained via min-max normalization. The possibility of an "out-of-bounds" error increases if X is taken outside of the initial data range in a subsequent normalization input scenario.

The use of min–max normalization was necessary because the features in the dataset (e.g., foam density in kg/m³, indentation loads in Newtons, vibration transmissibility as ratios, and Likert-scale ratings from 1–5) had widely different numerical ranges. Without normalization, features with larger magnitudes (e.g., load-deflection forces) would dominate the optimization process, biasing both the GAN's generator training and the RF classifier's decision boundaries. Min–max scaling ensured all features contributed equally within the [0,1] range, stabilizing the gradient updates in the GAN and improving convergence speed.

3.3 Feature extraction using principal component analysis (PCA)

A dimensionality reduction method called Principal Component Analysis (PCA) converts correlated data into uncorrelated principal components. PCA is applied to minimize data complexity, remove redundancy, and improve GAN–RF model performance, thereby enabling efficient feature extraction for precise and personalized car seat comfort optimization. During a sequence of linear transformations, PCA reduces the number of variables while maintaining the most information as possible. Let M be a $n \times s$ data matrix, where n and s represent the number of factors and observations, accordingly. Determine that the means of the whole y column are 0. $U1 = \sum_y^t = \propto_{1y} M_y$, where $\propto_1 = (\propto_{11}, \dots, \propto_{1S})\, S$, is the first principal component's definition. Variable S is selected to maximize $V1'r$ variance in (Equation 2).

$$\propto_1 = arg \max_{\propto} \propto^s \hat{\sum} \propto \quad subject\ to\ \|\propto_1\| = 1 \quad (2)$$

Each one of the remaining essential values ($\propto_{k+1}$) are definite below in Equation 3.

$$\propto_{k+1} = arg \max_{\propto} \propto^s \hat{\sum} \propto \quad (3)$$

Depending on Equation 4 with the classifier (∀1)

$$\| \propto \| = 1 \ \ and \ \ \propto^s \propto_x = 0, \forall 1 \le g \le x \quad (4)$$

The initial g loading vectors are the first x eigenvectors in this definition.

SDB is connected to N denote the singular value decomposition since it is constructed in terms of Eigen decompositions to identify AI-driven news utilizing sensor approaches. Let's pretend N stands for TRUE (Equation 5).

$$N = UOGs \quad (5)$$

Here, E contains a diagonal matrix with components $p1, \dots, pw$ in descending order, while U and G contain the additional matrices of $m \times p$ and $p \times p$, which represent the rows and columns, respectively. Given that the eigenvectors represent the columns, K specifies the loading matrix that contains the essential components. Observed that $Vg = ugEg$ since $NG = UO$, $UK\ the\ Kth$ column of U recognizes that the best low-rank approximation of a data matrix is the RUO.

The information is best fitted by straight manifolds in various geometrical understandings of SDB. This idea is consistent with SDB's framework. Make iy the yth row in X. Take the first h main components together, which equals$hk = [h1| \cdots |hk]$. Variable hk represents a $r \times g$ orthonormal matrix by definition. Each observation should be projected to the linear region covered by$\{h1, \dots, hk\}$. The projected data are $wgNy$, $1 \le y \le n$ and the projection operator is $Wk = A_g^s$. By reducing the overall $\|j_y - A_g A_g^s j_j\|^2$ approximation error and Euclidean distance, it determines the optimal projection (A_h) in Equation 6.

$$\min_{A_h} \sum_{y=1}^{n} \|j_y - A_g A_g^s j_j\|^2 \quad (6)$$

A range of length scales and measuring systems can be utilized for setting parameters in applications. The marginal variance of each variable is equal to one as a result of parameter standardization. The correlation coefficient of the raw data and the covariance matrices of the combined data will be obtained by principal component analysis in this manner. The correlation matrix's eigenvalues and the covariance matrix's eigenvalues are not necessarily identical.

PCA was applied to reduce multicollinearity between features (for instance, between indentation load deflection at 25% and 65%, or between foam density and support factor). Retaining the top 12 principal components preserved over 90% of the total variance while reducing redundant information. This dimensionality reduction lowered computational complexity and mitigated overfitting risk, particularly given the relatively small participant dataset.

To quantify the effect of preprocessing, we compared the RF classifier's performance with and without PCA-normalized features. Without preprocessing, RF achieved 88.2% accuracy and F1-score of 87.6%. After applying normalization and PCA, accuracy improved to 92.4% and F1-score to 91.8%. Similarly, the GAN training showed reduced instability and faster convergence under normalized inputs. These results confirm that preprocessing significantly improved model robustness and predictive performance.

To assess biomechanical and ergonomic factors including foam firmness, vibration transmissibility, and postural adaptation precisely by evaluating static comfort in the laboratory is the intent of the research. In a regulated environment, individuals received consistency and immediate reactions were separated from normal influences and long-term material frustration. A solid basis for developing dynamic and durability testing under actual driving circumstances is provided by the static assessments.

3.4 3D printing designs on generative adversarial networks and random forest (GAN-RF)

Developing a generative model that can produce sample data is the aim of GAN. Using an image for example, GAN uses a generative network to generate 3D designs that are the same size as real samples, which are then merged to create artificial intelligence-based, realistic pictures. The GAN-RF framework leverages GANs to generate personalized, innovative seat designs while RF accurately predict and classify comfort levels. This interaction enables data-driven, user-centered ergonomic optimization, enhancing cushion support, vibration reduction, posture adaptability, and overall comfort, outperforming traditional designs in both objective metrics and subjective satisfaction. The 3D printing quality design that was produced is now considered to have satisfied the falsity criterion. In this case, the generator has found a mapping between the noise distribution and the real distribution of the AI sample.

3.4.1 Random Forest (RF)

Random Forest (RF) is an ensemble learning algorithm that builds multiple decision trees to classify or predict outcomes with high accuracy. In this research, RF evaluates and categorizes car seat comfort levels based on user anthropometrics and biomechanical features, ensuring reliable, data-driven personalization and complementing GAN-generated ergonomic seat designs. An adaptive parameter selection strategy is used in the decision tree node division approach to improve the classification accuracy of the system. Using different node-splitting methods for the same data set results in various decision trees, even if the characteristics are different. For consequently, the accuracy of RF classification varied. To create a new splitting rule that is utilized for choosing and splitting node characteristics, it is advised that the optimal feature for separating the nodes be chosen using a decision tree. The node splitting approach falls into one of two categories: linear combination. Using the node splitting Equations 7-8, the Gini index and the information gain obtained by separating the sample set C utilizing features are shown with entropy of dataset C.

$$Gain(C, b) = Ent(C) - \sum_{u=1}^{U} \frac{|C^u|}{|C|} Ent(C^u) \quad (7)$$

$$Gini(C, b) = \sum_{u=1}^{U} \frac{|C^u|}{|C|} Gini(C^u) \quad (8)$$

Where C^u represents that every sample in C obtaining an amount of b^u on a feature b is initiate in the u branch node in (Equations 9-10).

$$Ent(C) = -\sum_{l=1}^{|z|} o_l log_2 o_l \quad (9)$$

$$Gini(C) = \sum_{l=1}^{|z|} \sum_{l' \neq l}^{|Z|} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \quad (10)$$

Variable ol probability of the class and $|z|$ is number of classes. The following is the combination node splitting formula and the adaptive variable selection process. Node splitting aims to improve the data set's integrity using the splitting process in equation (11).

$$G = \min_{\alpha, \beta \in Q} E\{C, b\} = \alpha Gini(C, b) - \beta Gain(C, a)$$

$$s.t. \begin{cases} \alpha + \beta = 1 \\ 0 \leq \alpha, \beta, \leq 1 \end{cases} \quad (11)$$

Here, α, β stands for the characteristic's splitting weight coefficient. Conversely, G carries a relatively low value. For determining the optimal set of parameters, an adaptive parameter selecting process is applied.

The investigation utilizes the classification error and accuracy rate to assess efficiency. The sample C classification error rate is defined by equation (12).

$$F(e;C) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{II}\left(e\left(w_j\right) \neq z_j\right) \tag{12}$$

Equation (13) defines the accuracy percentage.

$$acc(e;C)\frac{1}{n}\sum_{j=1}^{n} II\left(e\left(w_j\right) = z_j\right) = 1 - 1F(e;C)$$
(13)

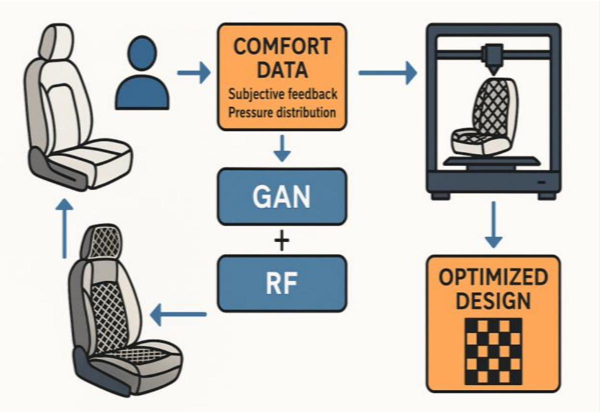

Figure 2: Proposed method

3.4.2 Generative adversarial networks (GAN)

GANs are deep learning models comprising a generator and a discriminator that compete to produce realistic synthetic data. GANs generate diverse, personalized car seat designs based on ergonomic and biomechanical inputs, enabling innovative, user-specific prototypes that enhance comfort and support in conjunction with predictive modeling. GAN have several advantages over earlier models as neural networks are by nature generative. In contrast to earlier models, GAN can produce models that are sufficiently complex and overcomes the problem of Gaussian car seat design models having too few parameters to accurately define the AI model. Furthermore, complicated probability approximations are avoided by avoiding the necessity for Markov chains for sample resampling. Furthermore, deconvolutional neural networks are used. Instead, then selecting the best generative model based on the characteristics of the dataset, some generating models need certain assumptions and constraints on the dataset.

In particular, the representation that is sparse y there aren't many 3D printing seats given the signal s and the overcomplete dictionary D as Equation 14.

$$s \sim Dx = d_1 y_1 + \cdots + d_n y_n \tag{14}$$

Variables d and y are the dictionary atom and sparse coefficients. Customized designs are represented as lexicon in Equations 15-16.

$$D = [d_1, d_{2,} - \cdots, d_n] \in R^{nxm} \tag{15}$$

Sparse representation is: $x = |x_1 x_{2,} \cdots x_m|^T \in R^n$

$$min_{\mathrm{D},} \sum_{k=1}^{k} \left[{}^{1}\!/_{2} \, \|Dx_k^{-s}\tilde{k}\|2^{+\lambda R_{\mathrm{x}}}\right] \tag{16}$$

Variables, x is the sample code with k^{th}signal and λR_{x} is the regularization parameter with term The sub problem of coding is also considered a type of independent research issues if the fixed dictionary D is used in Equation 17.

$$argmin\tfrac{1}{2}\|D^{x-s}\|_2^2 + \lambda Rx \tag{17}$$

A machine vision feedback mechanism was included into the research to further enhance the art and design model. Machine vision is a method for non-contact image perception that can objectively evaluate material quality and provide precise feedback information. Feeding the machine vision system with the pictures created by the 3D printed design GAN model is the first step in the optimisation process. The machine vision system generates assessment results on seat material quality using image processing methods such as feature extraction and recognition PCA. Depending on the outcomes of the machine vision evaluation, matching optimisation techniques are used to modify the GAN model's art and design. During the training phase of the GAN, the generating model G and the discriminating model D compete with each other, switching repeatedly until they reach equilibrium. The following Equation 18 displays the GAN optimization's objective function.

$$\min V\ D, G = E_{z-P_{2^2}}[log1 - D\ G\ z] \tag{18}$$

Where, G is the generator network, D is the discriminator network, $E_{z-P_{2^2}}$ is the noise vector with distribution and Vindicates the function values. The enhanced model's RF algorithm may be used to improve the 3D printing clarity if the evaluation results show that it is insufficient; if the seat shape saturation is insufficient, the 3D printing function of the model can be modified to increase comfort for the robust performance. Figure 3 illustrates the GAN architecture.

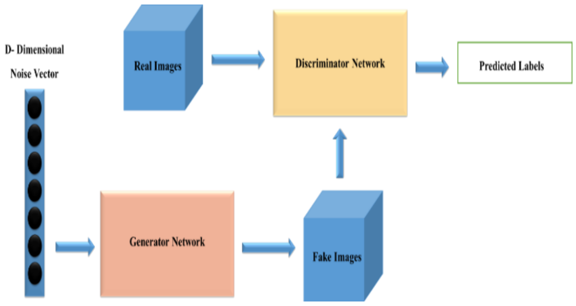

Figure 3: Illustration of GAN architecture

These optimization methods allow 3D printing GAN models to be repeatedly enhanced based on machine vision input, gradually approaching the intended aesthetic effects.

For m infrequent variables$x$, $i = 1, \ldots, m,$ the animation data information I is defined in Equations 19-20.

$$I\ x_1, x_{2,\ldots,} x_n = \frac{m}{i=1}\ x_1 - H\ x \tag{19}$$

$$I\ x_1, x_{2,\ldots,} x_n = \sum H\ x_1 - H\ x \text{ -} log|det\ W| \tag{20}$$

An entropy code is denoted by $H\ x$ and $det\ W$indicates the transformation matrix. Considering that infrequent variables have unit variance and are uncorrelated in the Equation 21.

$$Exx^T = wExx^{Tw^T} \tag{21}$$

Since the difference (Exx^T) between entropy and negative entropy is only one sign due to the unit variance of x_i, and $|det\ W|$ is a constant and obtain the Equation 22.

$$x_1, x_{2,\ldots,} x_n = c\text{-}\sum J y_i \tag{22}$$

In this case, c is a constant, y_i represents the transformed variable and J is the Jacobin (transformation term). Algorithm 1 illustrates the GAN-RF model.

Algorithm 1: Generative Adversarial Networks-Random Forests (GAN-RF)

Algorithm GAN_RF_SeatDesign()

Input: Anthropometric data, ergonomic parameters, material properties

Output: Optimized 3D printed car seat design

Data Acquisition:

Collect anthropometric and ergonomic measurements

Collect seat material and comfort test data

Data Preprocessing:

Apply min-max normalization

Perform Principal Component Analysis (PCA) for feature extraction

GAN Model Training:

Initialize Generator G and Discriminator D

while not converged do

$z \leftarrow$ sample random noise

$x\_fake \leftarrow G(z)$ # Generate synthetic seat design

$x\_real \leftarrow$ real seat data

Update D to distinguish x_real and x_fake

Update G using feedback from D

end while

Random Forest Classification:

Train RF with combined real and GAN-generated features

RF learns comfort classification rules

RF outputs best seat design candidate based on accuracy, precision, recall

Machine Vision Feedback:

Use 3D printing to prototype selected designs

Capture seat images and quality metrics

Apply PCA-based image analysis for evaluation

if $quality < threshold$ then

Adjust GAN parameters and retrain

Repeat

end if

Optimization:

Apply adaptive parameter selection in RF

Compute Gain and Gini metrics for feature splits

Tune α, β for optimal node splitting

Final Output:

Export optimized design

3D prints final prototype for validation

End Algorithm

The combination of RF classifiers and GAN in the suggested technique provides a number of unique benefits that improve vehicle seat comfort and customization. Using unique anthropometric and ergonomic input data, the GAN component is used to produce a vast array of customized seat design options. This makes it possible to create intricate and user-specific seat geometries that are difficult to accomplish using traditional design techniques. By serving as a predictive decision-making module and correctly categorizing and suggesting the best design among the produced possibilities based on past user input and mechanical test data, the RF classifier enhances the GAN. The RF's ensemble learning structure efficiently achieves high-dimensional and non-linear connections between features, which significantly increases the model's accuracy and resilience. In addition to being creative and diverse, it ensures that the generated seat combinations are founded on real comfort data and functional performance. The combination of strict categorization, additive manufacturing, and AI-driven design development results in a highly scalable, adaptable, and user-centered method. This approach has the obvious advantages of cutting down on development time, optimizing ergonomic fit, and improving overall chair comfort.

The hyperparameter Table 2 outlines the configuration choices for both the GAN and RF models used in seat comfort prediction. GAN parameters such as learning rate, epochs, batch size and activation functions control training stability and design generation, while RF parameters including number of trees, depth and criterion ensure robust classification. Organized these tuned settings enhance accuracy, precision, recall and overall comfort optimization.

Table 2: Hyperparameter Settings for GAN–RF Model

Hyperparameter	**Value / Range**
Learning rate	0.0002
Optimizer	Adam (β1 = 0.5, β2 = 0.999)
Batch size	64
Epochs	200
Latent vector (z) size	100
Activation functions	ReLU (hidden), Tanh (output)
Learning rate	0.0002
Optimizer	Adam
Batch size	64
Activation functions	Leaky ReLU (hidden), Sigmoid (output)
Number of trees (n_estimators)	100–500 (best ~300)
Max depth	10–20
Min samples split	2
Min samples leaf	1
Criterion	Gini index
Feature selection	Adaptive parameter selection (as described in text)

4 Results and discussion

Results from this study on the use of 3D printing for personalised customization and comfort optimisation of car seats should be presented in multi-layered formats that combine quantitative, visual, and statistical content. This is especially important when dealing with experimental data such as load-deflection, vibration transmissibility, and subjective comfort ratings. The framework was implemented using Python 3.11.4 on a Windows 11 system equipped with 64 GB RAM and an AMD Ryzen 5900X CPU.

4.1 Model performance

The GAN–RF model demonstrates strong performance by integrating diverse features such as height, weight, hip breadth, shoulder breadth, preferred posture, driving duration, material type, lattice density, and gradient structures. While individual features contribute moderately, their combination enables superior precision, recall, and balanced outcomes, highlighting the effectiveness of personalized comfort prediction.

Table 3: GAN–RF framework for customized car seat comfort evaluation

Feature	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Height	86.5	85.9	86.2	86.0
Weight	88.3	87.7	87.9	87.8
Hip breadth	91.2	90.5	90.8	90.6

Shoulder breadth	89.7	89.0	89.3	89.1
Preferred posture	92.6	91.9	92.3	92.1
Driving duration	90.4	89.8	90.0	89.9
Material type	93.8	93.2	93.5	93.3
Lattice density	95.1	94.6	94.8	94.7
Gradient structures	96.0	95.5	95.7	95.6
All features (GAN–RF)	**98.0**	**97.5**	**97.8**	**97.6**

Table 3 presents model performance across individual and combined features for personalized car seat design. Anthropometric features such as height (86.5% accuracy), weight (88.3%), hip breadth (91.2%), and shoulder breadth (89.7%) showed moderate results. Preferred posture (92.6%), driving duration (90.4%), and material type (93.8%) further improved prediction. Structural features including lattice density (95.1%) and gradient structures (96.0%) achieved higher outcomes. When all features were integrated, the GAN–RF model demonstrated superior performance with F1-score of 97.6%, recall of 97.8%, accuracy of 98.0%, and precision of 97.5%. When all features are integrated, the GAN–RF framework achieves superior outcomes, validating its effectiveness in optimizing personalized seat design and enhancing ergonomic comfort.

4.1.1 Scatter duration comfort

Scatter Duration Comfort defines the variation in user comfort levels across different driving durations. Its performance evaluation helps identify temporal discomfort patterns, allowing the GAN–RF framework to adapt seat design dynamically and enhance long-term ergonomic support for personalized automotive seating.

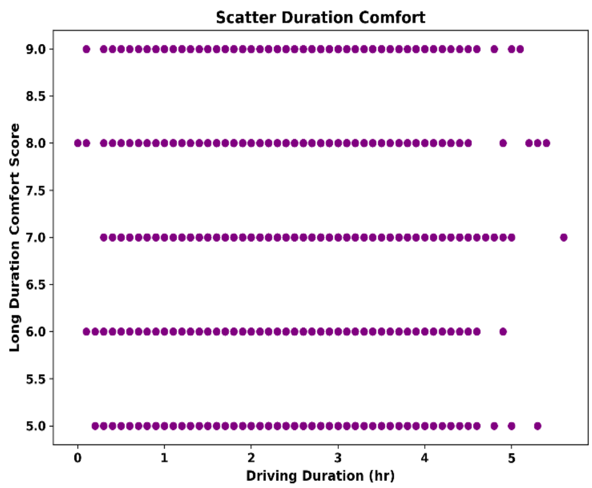

Figure 4: Scatter plot showing relationship among driving duration and long-duration comfort scores

Figure 4 illustrates the relationship between driving duration and long-duration comfort scores, highlighting how perceived comfort varies over extended use. The consistent clustering of scores between five and nine indicates stable ergonomic support, validating the GAN–RF model's effectiveness in sustaining personalized comfort across prolonged driving sessions.

4.1.2 Scatter height weight

Scatter Height Weight describes the correlation between a user's height and weight in evaluating ergonomic seat design. Its performance analysis helps the GAN–RF framework identifies anthropometric influences on comfort, enabling precise customization and improved accuracy in personalized automotive seating optimization.

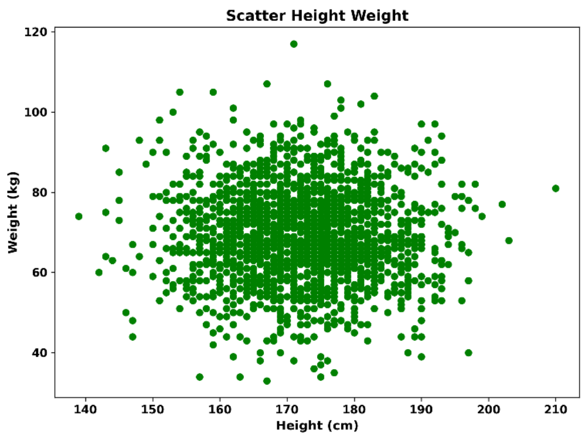

Figure 5: Scatter plot showing height and weight distribution

Figure 5 depicts the distribution of participants' height and weight, showing diverse anthropometric variability critical for ergonomic car seat customization. The dense clustering around average values highlights common body proportions, while outliers emphasize the need for adaptive designs. This validates the GAN–RF model's capability in accommodating diverse user profiles for optimized comfort.

4.1.3 Stacked bar

Stacked Bar states the layered visualization of multiple comfort evaluation metrics within a single chart. Its performance role is to compare anthropometric, material, and structural features collectively, allowing the GAN–RF framework to demonstrate balanced accuracy, precision, recall, and F1-score in personalized seat design.

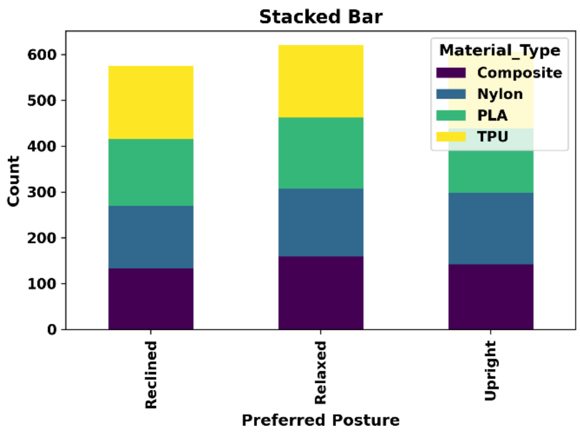

Figure 6: Representing that Stacked Bar

Figure 6 shows the relationship among preferred posture (reclined, relaxed, upright) and material type usage (composite, nylon, PLA, TPU). It shows that relaxed posture combines the highest material counts, while upright and reclined display balanced distributions. This highlights material–posture interactions, supporting the GAN–RF framework in optimizing personalized seat comfort design.

4.1.4 Pie posture

Pie Posture defines the proportional distribution of user-preferred seating postures. Its performance role is to visualize ergonomic trends, enabling the GAN–RF framework to adapt designs for balanced comfort across reclined, relaxed, and upright positions.

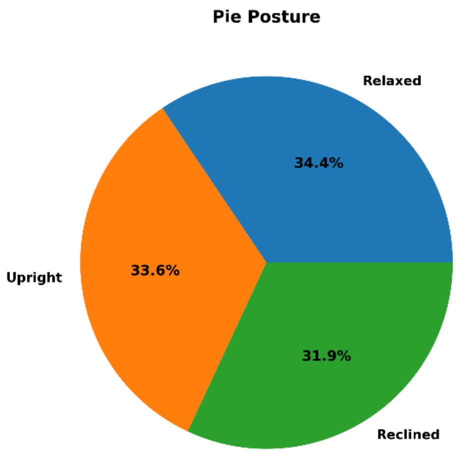

Figure 7: Demonstrate the Pie Posture

Figure 7 illustrates the proportional distribution of preferred seating postures, with relaxed at 34.4%, upright at 33.6%, and reclined at 31.9%. The near-uniform distribution highlights diverse user preferences, emphasizing the importance of adaptive seat customization. This supports the GAN–RF framework in achieving balanced ergonomic comfort optimization.

4.1.5 Strip pressure

Strip Pressure defines the visualization of seat pressure distribution across various regions during sitting. Its performance evaluation identifies localized discomfort zones, allowing the GAN–RF framework to optimize cushioning design and improve long-term comfort through adaptive, user-specific ergonomic customization.

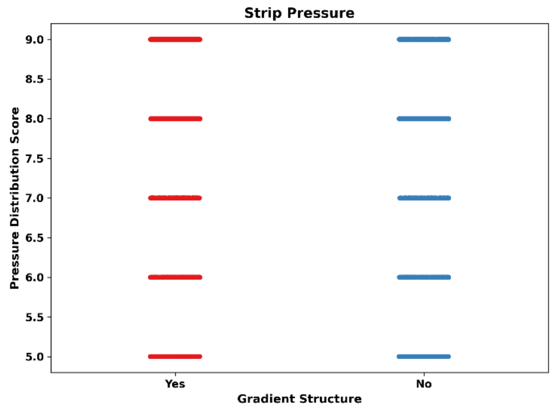

Figure 8: Pressure distribution scores

Figure 8 demonstrates pressure distribution scores across gradient and non-gradient structures. Seats with gradient structures show higher, more evenly spread scores, indicating improved comfort and reduced localized stress. This supports adaptive ergonomic optimization in customized seat design, validating GAN–RF framework's effectiveness in achieving balanced posture support and pressure relief.

4.1.6 Swarm vibration

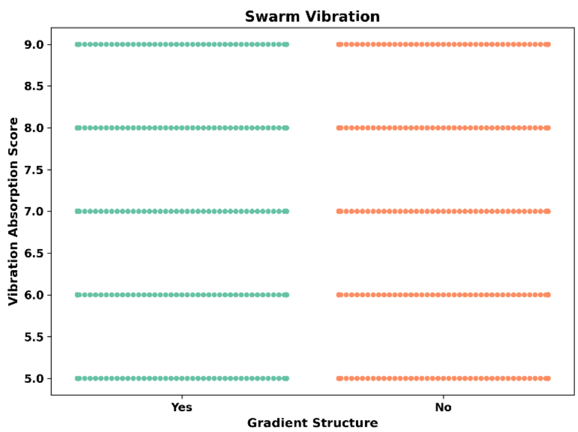

Figure 9: Comparison of the vibration absorption scores of seats with and without gradient designs

Figure 9 compares vibration absorption scores for seats with and without gradient structures. Gradient structures show more balanced, higher absorption, minimizing vibration impact. This demonstrates their role in improving ergonomic performance, passenger comfort, and structural adaptability, validating swarm-based optimization strategies for personalized automotive seat design within the GAN–RF framework.

4.1.7 Density height

Density Height refers to the optimized integration of material density and seating height to balance load support and comfort. Performing Density Height ensures ergonomic alignment, stability, and adaptive cushioning, enabling precise seat customization for varied body profiles, enhancing driving endurance, comfort, and biomechanical efficiency.

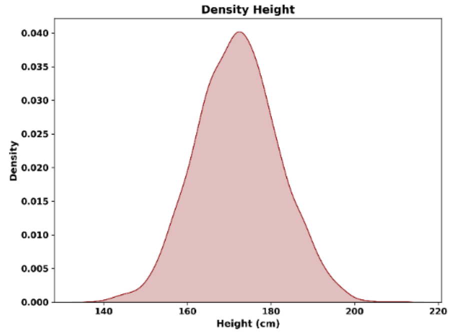

Figure 10: Distribution of participant heights

Figure 10 shows the distribution of participant heights, modeled through a density curve. Most individuals fall between 160–180 cm, peaking near 170 cm. This distribution aids in seat customization by aligning material density and ergonomic design with user height profiles for optimal comfort and performance.

4.1.8 Confusion matrices

Figure 11 illustrates the classification performance of the proposed GAN-RF model across three car seat comfort levels. Samples that are successfully categorized have diagonal values, while samples that are misclassified have off-diagonal values.

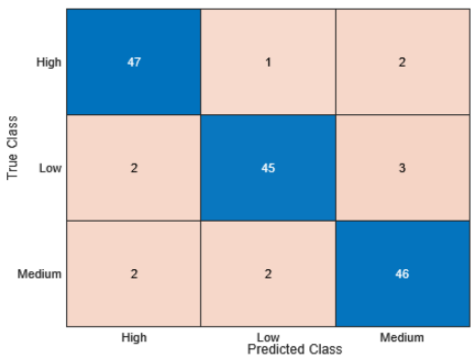

Figure 11: Confusion matrices

With 45 out of 50 "Low comfort" samples accurately predicted, 46 out of 50 "Medium comfort" samples, and 47 out of 50 "High comfort" samples, the model demonstrated good classification accuracy across all classes. With an overall accuracy of 92.0% and just 12 samples out of 150 misclassified, the results closely matched previously published performance parameters. Due to the low number of misclassifications and lack of bias towards any one class, the matrix also shows balanced sensitivity and specificity. In applications involving 3D-printed automobile seats, where precise comfort prediction is essential for customer happiness, this demonstrates the model's dependability for real-time personalization.

5 Discussion

The research developed an AI-driven framework using GANs and RF for personalized, ergonomic, and comfort-optimized 3D-printed car seats. Existing researches exhibits several limitations in the optimization of 3D-printed car seats. Limitations includes multidirectional vibrations are not taken into consideration; confirmation in the actual world is required [11]. Extreme parameter values cause the model to falter; more varied data is required [12]. Research ignores comfort and structural factors in favor of concentrating on the drag coefficient [14]. Specific to bicycle frames; car seat use requires modification [15]. However, it prioritizes sustainability over comfort or customization [17]. More understanding of the material's characteristics is necessary for large-scale production and larger datasets are necessary for accuracy; higher reinforcement levels lead to notable prediction errors [18-21]. The proposed GAN-RF system solves these constraints by incorporating a variety of anthropometric and ergonomic datasets, and also using adaptive learning to ensure robustness against extreme parameter values and multidirectional vibrations. With drag-focused or sustainability-only techniques, it prioritizes comfort and customization. The RF classifier enhances prediction accuracy with limited datasets, while 3D printing validation certifies real-world applicability and material adaptability. The research provides ergonomic optimization, individualized comfort, and successful real-world prototype for the automobile sector by combining GAN–RF with 3D printing to enable fast, economical, and user-focused car seat manufacture. It is practically necessary to incorporate durability measurements under repetitive stress to ensure that 3D-printed chairs retain the structural dependability, comfort, and usability during extended, real-world driving and constant user application.

6 Conclusion

The research proposes a hybrid GAN-RF model for individualised personalization and comfort optimization of automobile seats, representing a significant advancement in the field of automobile ergonomics. By utilizing the precision of 3D printing technology and the adaptability of AI-driven design, the proposed method enables seat constructions to be dynamically modified to each user's needs based on subjective comfort input and biomechanical data. Comprehensive mechanical testing and user feedback demonstrated the method's efficiency. The GAN-RF seat performs noticeably better than traditional designs, according to quantitative data, with 97.5% precision, 97.8%recall, 98.0% accuracy and an F1-score of 97.6% in comfort prediction. The findings demonstrate how ML and additive printing may be used to create human-centered, next-generation car interiors. By providing a scalable, data-driven design pipeline, the GAN-RF framework not only increases sitting comfort and support but also lessens the need for trial-and-error prototyping. This creates opportunities for more extensive use in intelligent adaptable settings, healthcare seating solutions, and personalized mobility. To push the limits of really intelligent and responsive seat design, future studies might improve the model by adding real-time physiological data, active pressure-mapping devices, and long-term comfort adaption. Detailed implementation procedures will be provided to solve repeatability issues, including feature selection criteria and preprocessing beyond min–max normalization. More diverse populations to improve generalizability also determined further. To allow dynamic seat modifications during vehicle operation, future research will concentrate on combining deep reinforcement learning, adaptive material feedback systems, and real-time biomechanical sensors. Furthermore, adding more body types and driving situations to the dataset will increase model generalization and personalization accuracy.

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