Textile & Leather Review

ISSN 2623-6281| www.tlr-journal.com | 10.31881/TLR

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How to cite: PÉREZ-CORONA G, ARIAS-AGUILAR JA, RAMÍREZ-GUZMÁN ME. Pattern Customization Using Neural Networks. Textile & Leather Review. 2026; 9:1036-1052. https://doi.org/10.31881/TLR.2026.1036

How to link: https://doi.org/10.31881/TLR.2026.1036

Published: 27 April 2026

Pattern Customization Using Neural Networks

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Article

https://doi.org/10.31881/TLR.2026.1036

Received 17 December 2025; Accepted 24 February 2026; Published 27 April 2026

ABSTRACT

In the fashion industry, patterns play a fundamental role as they constitute the structural foundation of any garment. Although technological advances have facilitated the digital pattern-making process, this work still largely depends on the experience and knowledge of skilled designer-pattern makers. Training an expert pattern maker requires significant investment of time and resources from companies. In this context, we present an innovative approach for personalized pattern construction, supported by 15 years of experience on pattern making and machine learning programming. Our elaboration process for basic women's patterns (front and back bodice) is based on industrial and custom patternmaking knowledge, using 13 structural measurements of the female body as input to a neural network model who generates a personalized pattern as output. The potential benefits of our approach are multiple. It can not only help nonexpert designers create personalized patterns but also improve time efficiency for experienced designers. Furthermore, our model facilitates the transition to industrial-scale applications, enabling companies to reduce their dependence on expert pattern makers and promote efficiency in the pattern-making process.

KEYWORDS

pattern customization, neural networks, digital patternmaking

INTRODUCTION

Recent technological progress has reshaped the fashion industry, positioning digital patternmaking as a key driver of innovation. Nevertheless, the automation of personalized garment pattern generation remains an open challenge, requiring robust theoretical foundations and advanced computational methods to ensure practical success.

Clothing, as an essential product that integrates physiological protection, mobility support, and self-expression [1], has evolved beyond its basic functional role to encompass social significance, individual identity, and self-realization. This evolution has shifted the act of clothing selection toward a personalized process that emphasizes fit, fashion, and self-expression [2]. With the rapid expansion of e-commerce, consumer demand for personalized products has intensified [3]. As a result, traditional analog and manual customization systems, constrained by lengthy production processes, have become insufficient. Addressing this gap requires the development of a personalized pattern-making model grounded in solid theoretical principles and supported by technical innovation [4].

Rising material and cultural living standards have further elevated consumer expectations, rendering traditional mass-production methods inadequate to meet demands for individuality and fashion [5]. The reliance on standardized garment sizes exacerbates this issue. As highlighted in [6], the European e-commerce market faces significant challenges due to product returns, with size-related fit problems accounting for between 41% and 81.7% of cases. This high return rate generates consumer frustration, as shoppers struggle to determine appropriate sizes and encounter inconsistencies across brands.

Consumers increasingly invest in garments that reflect their identity, with heightened expectations for fashion design and a desire to actively participate in the personalization process [7]. Since custom-made clothing better accommodates individual needs in terms of style, fabric, and fit, fashion companies are prioritizing strategies to achieve accurate garment fitting. In this context, the technical expertise of designers plays a decisive role in determining the quality and form of custom-made garments [8].

Artificial Intelligence (AI) algorithms, particularly Graph Neural Networks (GNNs), offer significant potential to address these challenges. Their inherent structure of nodes and edges aligns naturally with the lines and vertices used in traditional pattern construction, making them well-suited for digital pattern development.

Building on the integration of computer-aided design systems with recent advances in AI, this research proposes a prototype system for pattern construction supported by artificial neural networks. The system enhances efficiency and quality in the development of custom pattern structures, reduces dependence on operator expertise, and shortens development time. By leveraging the learning, self-organization, and adaptive capabilities of neural networks, the proposed approach enables the automated generation of customized basic torso pattern structures for women’s garments.

Methods

For this research, Alan's V-cycle methodology [9] was adopted. This approach, grounded in principles of staged validation and verification, ensures both the quality of the final product and the correct execution of the development process.

Problem Statement

In the initial stage of the project, the need was identified to develop a prototype of a personalization system based on neural networks, designed to construct custom-made bodice patterns for women. The objective was to generate personalized patterns derived from specific anthropometric measurements. To achieve this, a preliminary study was conducted on the standard values of American industrial patternmaking, establishing a correspondence between industrial measurements and those required to define personalized bodices. As a reference, the American industrial measurement table shown in Figure 1 was employed. These measurements make it possible to construct complete female bodice patterns (front and back) across different sizes, as illustrated in Figure 2.

American System Measurement Chart

Front and Back Bodice Measurement Chart

Bodice Front									
SIZES	0	3	5	7	***9***	11	13	15	17
1.- Front bodice length	16 ¼"	16 ½"	16 ¾"	17"	***17 ¼"***	17 ½"	17 ¾"	18"	18 ¼"
2.- 1/4 bust circumference	8 ½"	8 7/8"	9 ¼"	9 5/8"	***10"***	10 3/8"	10 ¾"	11 1/8"	11 ½"
3.- Horizontal neck line	2 7/16"	2 ½"	2 9/16"	2 5/8"	***2 11/16"***	2 ¾"	2 13/16"	2 7/8"	2 15/16"
4.- Vertical neck line	2 ¾"	2 7/8"	3"	3 1/8"	***3 ¼"***	3 3/8"	3 ½"	3 5/8"	3 ¾"
5.- Bust point separation	3 ¼"	3 3/8"	3 ½"	3 5/8"	***3 ¾"***	3 7/8"	4	4 1/8"	4 ¼"
6.- Side seam length	7 1/8"	7 ¼"	7 3/8"	7 ½"	***7 5/8"***	7 ¾"	7 7/8"	8	8 1/8"
7.- 1/4 waist circumference	5 ¼"	5 5/8"	6"	6 3/8"	***6 ¾"***	7 1/8"	7 ½"	7 7/8"	8 1/4"
8.- Waist to shoulder	13 1/8"	13 3/8"	13 5/8"	13 7/8"	***14 1/8"***	14 3/8"	14 5/8"	14 7/8"	15 1/8"
9. -Shoulder length	4 3/8"	4 ½"	4 5/8"	4 ¾"	***4 7/8"***	5"	5 1/8"	5 ¼"	5 3/8"
Bodice back									
10.- Half back circumference	7 ½"	7 7/8"	8 ¼"	8 5/8"	***9"***	9 3/8"	9 ¾"	10 1/8"	10 1/2"
11.- Center back length	15 ½"	15 ¾"	16"	16 ¼"	***16 ½"***	16 ¾"	17"	17 ¼"	17 ½"
12.- Horizontal neck line	2 7/16"	2 ½"	2 9/16"	2 5/8"	***2 11/16"***	2 ¾"	2 13/16"	2 7/8"	2 15/16"
13.- 1/4 waist circumference	5 ¼"	5 5/8"	6"	6 3/8"	***6 ¾"***	" 7 1/8	7 ½"	7 7/8"	8 1/4"
14.- Half back	6 3/8"	6 9/16"	6 ¾"	6"	***7 1/8"***	7 5/16"	7 ½"	7"	7 7/8"

Figure 1. Table of the 14 female torso measurements from the American industrial system

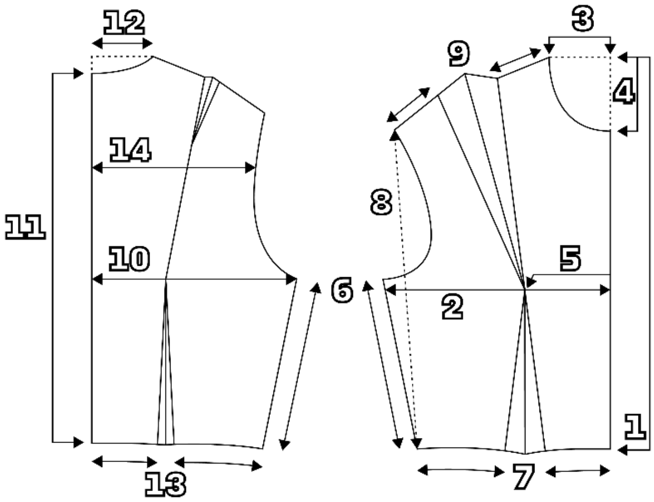

Figure 2. Female bodice patterns using American industrial system measurements

Custom Bodices

Human bodies present a wide range of shapes, proportions, and distributions of body mass that are not always reflected in the standardized measurements employed by the fashion industry. Moreover, shifting size trends over time, the lack of standardization across brands and manufacturers, the prioritization of aesthetics over fit, ethnic and geographic differences, and changes in average body dimensions all contribute to discrepancies between graded sizes and actual bodies [10].

The 3 Octavos Fashion House (Puebla, Mexico) developed a simplified method for adapting industrial patterns into custom-made patterns, which served as the foundation for the computational system proposed in this research. This method transforms an industrial bodice model into a personalized pattern in approximately 50 steps, using seven measurements from the American industrial system along with six additional female torso measurements.

The seven industrial measurements forming the basis of the personalization system are:

• Waist length

• Bust circumference

- High point
- Waist circumference
- Shoulder length
- Center back length
- Back width

The six complementary measurements for developing a custom-made pattern are:

- Bust depth
- Center length
- Front shoulder separation
- Bust point distance
- Back length from shoulder
- Back shoulder separation

Together, these anthropometric measurements define the structure of personalized bodices. As illustrated in Figure 3, they capture thirteen key regions of the body that reflect the proportions and curves of each woman’s torso.

Not all measurements are applied directly during the construction of personalized patterns. Length measurements are incorporated as recorded, while others, such as bust and waist circumference, must be divided into quarters. Similarly, measurements such as front and back shoulder separation, high point, bust point distance, and back width are halved before being applied in the design process. Figure 4 illustrates the set of measurements collected for one participant.

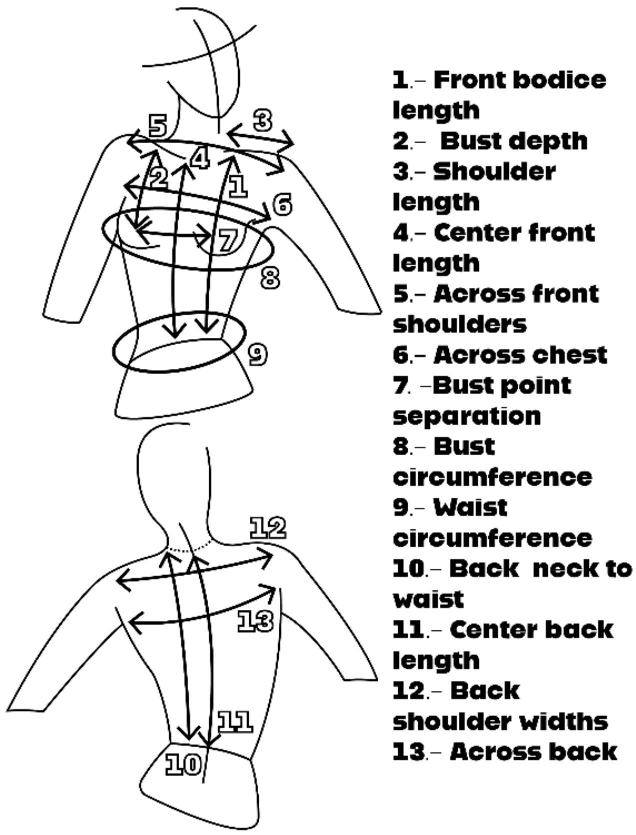

Figure 3. Female bodice patterns

FRONT BODICE	MEASUREMENTS	BACK BODICE	MEASUREMENTS
1.- Front bodice length	45	10.- Back neck to waist	40.5
2.- Bust depth	30	11.- Center back length	37.5
3.- Shoulder length	13	12.- Back shoulder widths	40/2=20
4.- Center front length	34.5	13.- Across back	36/2=18
5.- Across front shoulders	41/2=20.5		
6.- Across chest	38/2=19		
7. -Bust point separation	19/2=9.5		
8.- Bust circumference	105/4=26.25		
9.- Waist circumference	84/4=21.5		

Figure 4. Sample of individual measurements in our database

Once the thirteen structural measurements required by the 3 Octavos method were defined, the data collection phase began. This fieldwork involved measuring 200 women (75 in Huajuapan de León, Oaxaca, and 125 in the metropolitan area of Puebla) to capture a wide variety of body types and sizes. The resulting data were organized and stored in a structured database, serving both as an information repository and as the basis for subsequent analysis and processing.

For training the neural networks corresponding to the front bodice we used 10 measures: front bodice length, bust depth, shoulder length, center front length, across front length, across chest, bust point separation, bust circumference, waist circumference, and ¼ of bust circumference. For the back bodice we used 8 measures: front bodice length, shoulder length, bust circumference, ¼ of bust circumference, back neck to waist, center back length, back shoulder widths, and across back.

Anthropometric Data

Anthropometric data collection was conducted with care to ensure accuracy and consistency. Analyzing these measurements is essential for understanding the anthropometric variability of women in Huajuapan and Puebla. For example, in the case of waist length, the most frequent measurement was 41 cm, recorded in 31 participants (16% of the total sample), followed by 42 cm in 26 cases (13%) and 44 cm in 23 cases (12%). Together, these three values account for 41% of the sample (see Figure 5).

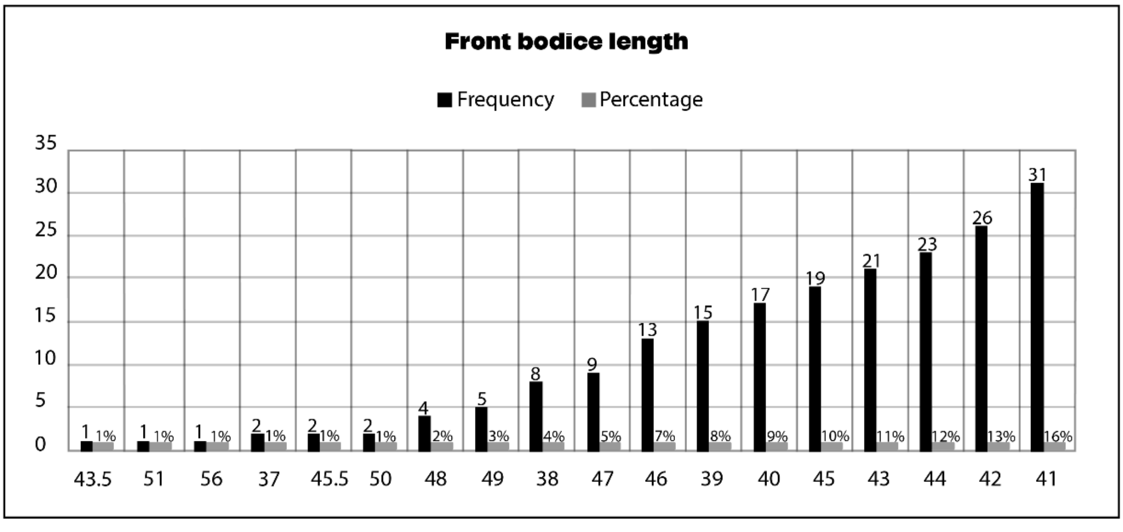

Figure 5. Distribution of waist length measurement

Bust depth data revealed a slightly different distribution pattern, with greater concentration around the modal values of a skewed distribution. The predominant measurement was 26 cm, recorded in 47 cases (24%), followed by 28 cm in 38 participants (19%) and 27 cm in 31 cases (16%). This concentration in the 26–28 cm range encompasses 59% of all participants (see Figure 6).

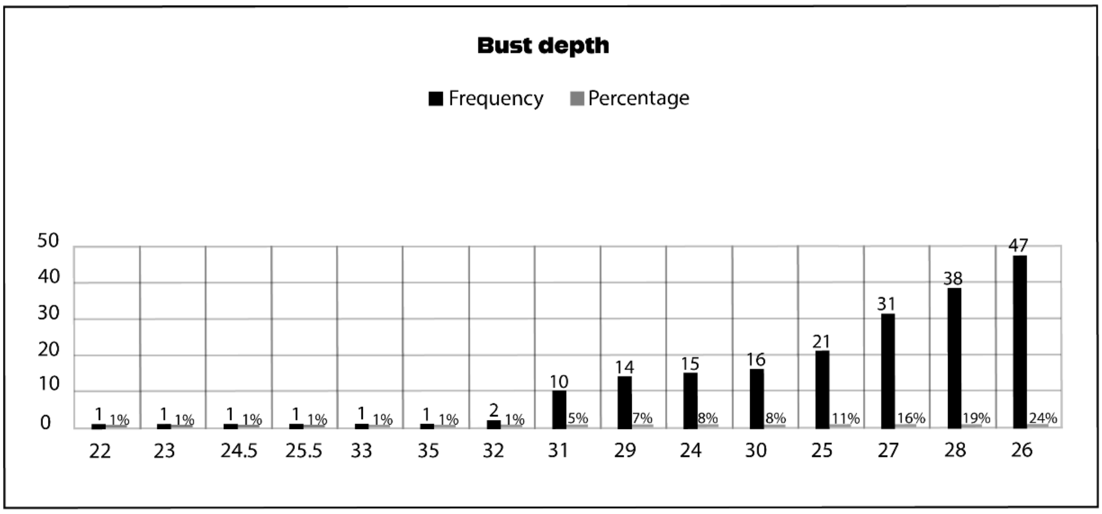

Figure 6. Distribution of bust depth measurement

These data distributions have direct implications for the computational system, as the neural network must adapt the base pattern (size 9) to account even for less common measurements with lower representation in the sample. The age range of the participants in the project was set between 20 and 45 years because this period encompasses a stage of relative stability in female body proportions. Among the 200 participants, we captured a diversity of body types that can be classified as 50% considered "slim", 40% considered "average," and 10% considered "large."

Digital Patterns

Once the anthropometric database was established, a process was defined for constructing and segmenting each bodice into triangles, ensuring compatibility between the structure of a bodice and the output of the neural network. Graph Neural Networks operate internally with nodes and edges, while patternmaking relies on lines and vertices. Efficient segmentation of bodices into triangles and the generation of an appropriate data structure for information representation are therefore fundamental for training the neural network and producing personalized patterns.

For the back bodice, segmentation was defined into 24 triangles connected by 27 nodes, while the front bodice was segmented into 27 triangles connected by 25 nodes (Figure 7). Each triangle and node was carefully positioned to capture variations in body shape. Throughout the research, different segmentations and measurements were generated and evaluated to identify the optimal configuration that would capture the essence of the pattern structure without redundancy.

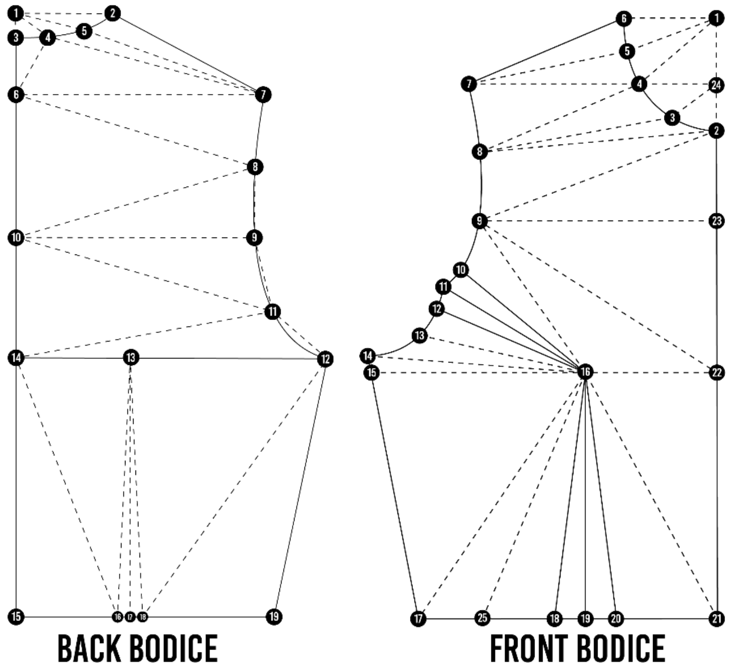

Figure 7. Segmentation of bodices into triangles

Neural Network Training

At this stage, several variants of neural networks were trained, some dedicated to the front bodice and others to the back bodice. In the training process, the network inputs consisted of the vector of individual body measurements combined with the adjacency matrix of the reference pattern derived from size 9, while the outputs corresponded to the adjacency matrices of the personalized patterns. In other words, given a person's measurements, the network learned to modify the reference pattern and transform it into a customized pattern (Figure 8).

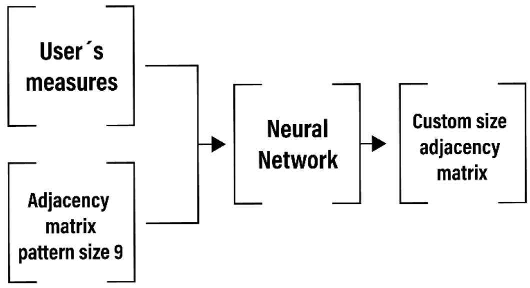

Figure 8. Input-Output entries of the designed system

Of the 200 available examples, 190 were used for training and 10 for validation, ensuring that the network was capable of adapting patterns it had not previously encountered.

Front Bodice

The first network model trained was a multilayer perceptron (MLP). After exploring different hyperparameter values in a mesh search procedure, the configuration that produced the best results included:

• 1 input layer with 37 neurons

• 3 hidden layers with 256 neurons each

• 1 output layer with 27 neurons

• 'elu' activation functions in the hidden layers

• Adam optimizer with a learning rate of 1e-03

• Loss function: Mean Squared Error

• Batch size: 5

• 200 epochs

• 148,251 trainable parameters

The second model explored as part of the solution was an Encoder–Decoder neural network. The hyperparameters of the best-performing configuration were:

• 1 input layer with 27 neurons

• An encoder with 4 hidden layers of 128, 64, 32, and 16 neurons

• Concatenation of the encoder's final layer with a vector of 10 measurements

• A decoder with 3 hidden layers of 32, 64, and 128 neurons

• 1 output layer with 27 neurons

• 'elu' activation functions in the hidden layers

• Adam optimizer with a learning rate of 1e-03

• Loss function: Mean Squared Error

• Batch size: 5

• 500 epochs

• 29,227 trainable parameters

Back Bodice

The best-performing MLP model for the back bodice presented the following configuration:

• 1 input layer with 38 neurons

• 3 hidden layers with 256 neurons each

• 1 output layer with 30 neurons

• 'elu' activation functions in the hidden layers

• Adam optimizer with a learning rate of 1e-03

• Loss function: Mean Squared Error

• Batch size: 5

• 200 epochs

• 149,278 trainable parameters

The best-performing Encoder–Decoder model for the back bodice was defined by the following hyperparameters:

• 1 input layer with 30 neurons

• An encoder with 4 hidden layers of 128, 64, 32, and 16 neurons

• Concatenation of the encoder's final layer with a vector of 8 measurements

• A decoder with 3 hidden layers of 32, 64, and 128 neurons

• 1 output layer with 30 neurons

• 'elu' activation functions in the hidden layers

• Adam optimizer with a learning rate of 1e-03

• Loss function: Mean Squared Error

• Batch size: 5

• 500 epochs

• 29,934 trainable parameters

RESULTS AND DISCUSSION

Table 1 presents the training results of the networks corresponding to the front bodice. Overall, the Encoder–Decoder topology achieved better performance, with lower test errors compared to the multilayer perceptron (MLP).

Table 1. Results of neural networks trained for the front bodice

Network type	MSE Train Error	MSE Test Error
MLP	0.1027 ± 0.0134	0.0995 ± 0.0164
Encoder-Decoder	0.0733 ± 0.0102	0.0774 ± 0.020

To assess the significance of these quantitative results, Figure 9 provides a visual comparison of front bodice meshes for two test examples from the database (examples 191 and 195). The figure shows the manually created custom mesh alongside the reconstructions generated by the MLP and Encoder–Decoder networks.

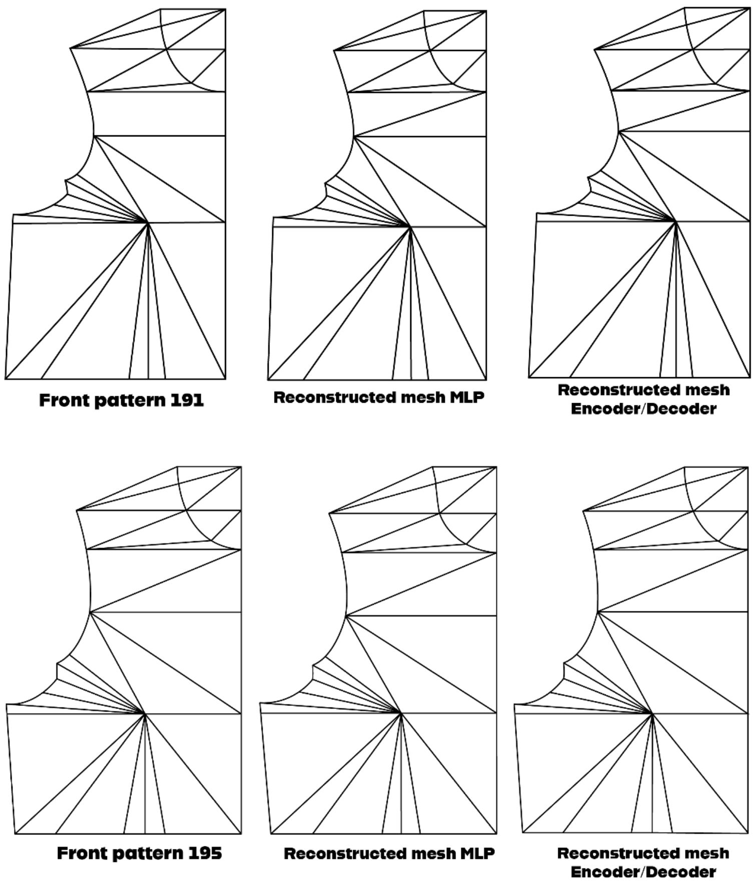

Figure 9. Reconstruction of front bodice meshes

The results for the back bodice are shown in Table 2. The Encoder–Decoder again outperformed the MLP, although the back bodice proved more difficult to model than the front. Figure 10 illustrates a visual comparison of back bodice meshes for two test examples (examples 198 and 200).

Table 2. Results of neural networks trained for the back bodice

Network type	MSE Train Error	MSE Test Error
MLP	0.2616 ± 0.0459	0.3469 ± 0.0547
Encoder-Decoder	0.1617 ± 0.0145	0.2675 ± 0.0164

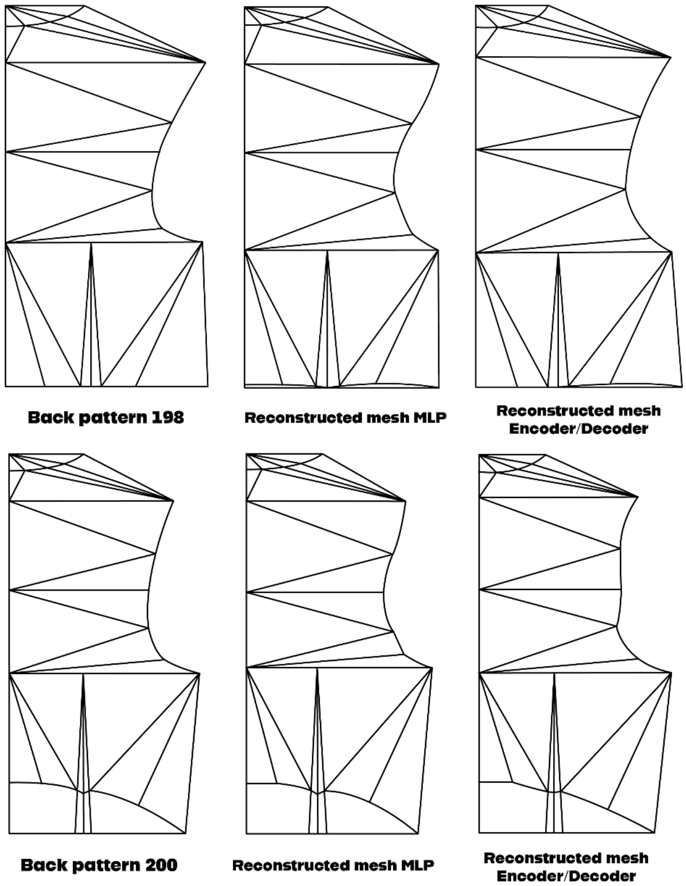

Figure 10. Reconstruction of back bodice meshes

At the qualitative level, both models demonstrated a similar ability to reconstruct the fundamental characteristics of personalized bodices from user measurements. However, small distortions were observed, particularly in joint areas and inflection points. These distortions were more evident in the front bodice than in the back, confirming the greater structural complexity of the back pattern and the challenges it poses for neural network architectures.

CONCLUSION

This study confirmed the feasibility of developing a prototype digital pattern-making application supported by neural networks, capable of improving fidelity and simplifying the creation of personalized patterns.

The comparison between two network topologies— Multilayer Perceptron (MLP) and Encoder–Decoder— revealed differences in their processing and reconstruction capabilities. In particular, the Encoder–Decoder architecture demonstrated superior performance in handling bodice patterns, largely due to its use of fewer trainable parameters.

It was also observed that the reconstruction of the front bodice yielded lower error rates in both architectures, suggesting that the morphological complexity of the female back presents additional technical challenges that require special consideration in the design of future systems.

The analysis of anthropometric frequencies from the 200 participants provided a deeper understanding of body proportions and valuable insights for the development of the automated patternmaking system. The findings revealed anatomical correlations among different body measurements, establishing proportional relationships that transcend regional differences between Oaxaca and Puebla. Structural measurements such as shoulder length and high point showed the highest concentrations, with 84% and 60% of cases, respectively. In contrast, circumference measurements such as bust and waist exhibited the greatest variability, validating the need for personalization in these dimensions to achieve proper garment fit. Notable discoveries include the consistent 9–10 cm difference between waist length and centre length, confirming the influence of bust volume on longitudinal measurements; the correlation between back length from shoulder and back shoulder separation, suggesting natural square proportions in back structure; and the 2–3 cm differences between bust point distance and back width, reflecting anatomical variations between these body regions.

The system developed demonstrates significant potential to transform the field of personalized patternmaking. Its ability to automatically generate customized patterns with acceptable levels of accuracy suggests that this technology could contribute to democratizing access to personalized garments and optimizing processes within the textile industry. Such advances may enhance the competitiveness of less-experienced designers while strengthening efficiency in the national textile sector.

Future work should focus on completing the application's development, expanding measurement datasets to include a broader range of sizes, incorporating other garment types, and refining network models to address the identified complexities. These efforts will consolidate the system as a tool that responds to the needs of the personalized sector and positions Mexico as a contributor to technological innovation in fashion design.

Author Contributions

Conceptualization – G. Pérez-Corona and J. Arias-Aguilar; methodology – G. Pérez-Corona, J. Arias-Aguilar and M. Ramírez-Guzmán; formal analysis – G. Pérez-Corona and J. Arias-Aguilar; investigation – G. Pérez-Corona; writing-original draft preparation – G. Pérez-Corona and J. Arias-Aguilar; writing-review and editing – J. Arias-Aguilar; visualization – M. Ramírez-Guzmán; supervision – J. Arias-Aguilar. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding

Human Research Subjects

All individuals involved in taking the anthropometric measurements necessary for the creation of the project database acted in a consensual manner and their identification has been anonymized.

Acknowledgements

We gratefully acknowledge the support of the Consejo Nacional de Humanidades, Ciencia y Tecnología (CONAHCyT) for the financial assistance and opportunity provided to carry out this project within the framework of the Master's Program in Fashion Design at the Universidad Tecnológica de la Mixteca.

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