A Machine Learning Model to Optimize Bomb Suit Size Selection

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Abstract. Given their high complexity and cost, bomb suits are often shared among bomb squads or military units. For any given suit size, personalized fit is possible through various adjustment systems, to accommodate a wide range of body sizes and types. While sizing tables based on height and weight are provided by manufacturers to facilitate size selection, variances in body shapes, or morphotype, are such that sizing charts do not always provide the best sizing recommendation. A total of 177 volunteers were sized (height and weight) and then fit in the most appropriate size of bomb suit by a sizing expert, taking wearer preferences into account. The predictions from the standard sizing chart were first compared with the users' preferences, with a relatively low success rate (68%). A decision tree algorithm was then applied to optimize the predictions based on solely height and weight, yielding an improved success rate of 85%. Considering that bomb suit size selection is governed by more than just height and weight, a smartphone application was then used to generate an avatar and estimate 83 body measurements, based on two photos from each volunteer (front and profile views). The output from this app was then fed into a multinomial regression machine learning model to provide suit size recommendations that were more precise than those obtained from the basic sizing chart (prediction success rate of 92%). The multinomial regression model was thus found to outperform both the standard legacy sizing chart and the decision tree that had been based on solely the height and weight of an individual. In addition, the multinomial regression model provided independent predictions for the trousers and jacket, whereas the legacy chart was developed to predict the overall suit size.

1. INTRODUCTION

Personal Protective Equipment (PPE) for military applications is typically designed to accommodate the widest possible range of male and female personnel, while minimizing the number of sizes [1]. This approach balances substantial development costs and logistical challenges, which are particularly significant for military use. These cost challenges are further amplified in the case of bomb suits due to the high expense of moulds for hard armour and the lower production volumes for such specialized equipment compared to standard soldier PPE.

Bomb suits are rarely issued as personal items and are instead often shared among multiple operators. This shared usage necessitates a broader fit for each suit size to accommodate a wider range of users. The US National Institute of Justice (NIJ), through its NIJ 0117.01 standard for public safety bomb suits [2], mandates that manufacturers provide at least three distinct sizes to accommodate users, while specifying maximum weights for each suit size.

Bomb suits are more complex than traditional military fragmentation vests, often consisting of three main components: a helmet, jacket, and trousers. These elements must not only fit properly but also function seamlessly together. To accommodate diverse body types within a limited number of sizes, bomb suits include adjustable features like hook-and-loop closures, straps, and other attachments. Despite these features, some bomb technicians may not fit into any standard size. While customized sizing for such outliers is theoretically possible, as discussed by Flynn et al. [3], the economic feasibility of this solution is often limited, leaving some technicians without adequately fitted PPE.

Manufacturers typically provide sizing charts based on height and weight to assist users in selecting an appropriate size. However, these two parameters fail to capture significant variations in body shapes. Individuals with the same height and weight may have vastly different body dimensions and require different suit sizes. For example, Kozey et al. [4] found that limb lengths and circumferences play a critical role in proper sizing for immersion suits used by law enforcement and the military. Consequently, sizing charts based solely on height and weight might lead to suboptimal recommendations.

As Choi et al. [1] emphasize, PPE development should address sizing issues early in the design process to ensure proper functionality and fit [5]. Their proposed approach includes identifying design problems related to the item's concept, function, and fit based on anthropometric data, followed by iterative prototype development and testing. The final step involves producing products in all necessary sizes, along with a comprehensive sizing chart and tariff. This process aims to achieve high accommodation rates for both males and females while minimizing the number of sizes.

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Figure 1. An NIJ-certified bomb suit ensemble from Med-Eng

However, not all products are developed using this systematic approach. In such cases, sizing charts must be refined retrospectively. This study focuses on a Med-Eng (Ottawa, Canada), bomb suit (Figure 1), an NIJ 0117.01 certified system which is currently offered in four predefined sizes. The objective is to develop optimized sizing tools for this bomb suit using anthropometric measurements and sizing trials from a large sample of volunteers and applying classification algorithms. The analysis will focus on the suit's jacket and trousers, excluding the helmet.

2. METHODS

A fitting exercise was conducted for the bomb suit, involving 177 volunteers whose height and weight were measured (Figure 2). Under the guidance of a bomb suit sizing expert, the best-fitting sizes for the bomb suit jacket and trousers were determined for each participant through dressing trials. The trials also assessed whether individuals would benefit from the trousers' "leg expanders" feature (Figure 3) to account for larger waist and lower body dimensions (larger leg diameter).

In addition to manual height and weight measurements, further sizing data were collected using an Android-based sizing application, XpertFit (Safariland, Jacksonville, FL). This app captures two photos of each participant (frontal and profile views) while they wear tight-fitting clothing. After height and weight are entered manually, the app's algorithm generates an avatar (Figure 4) and estimates 83 body measurements, including arm length, chest circumference, thigh length, and more.

Initially, the preferred user sizes obtained from dressing trials were compared with the manufacturer's existing sizing chart (Figure 5). Using the preferred sizes, an improved sizing chart was created through a decision tree model. The CART decision tree algorithm, as described by Duda et al. [6], was implemented in MATLAB and used height and weight as the sole input variables. A separate decision tree was constructed to determine the need for leg expanders, also based exclusively on height and weight.

Recognizing that bomb suit sizing might depend on more than just height and weight, a multinomial regression machine learning model inspired by Dionne [7] was developed. This model utilized the 83 body measurements collected via the XpertFit app. The model generates a linear equation with weighted coefficients for each measurement, optimizing the fit selection based on the preferred suit sizes identified during the dressing trials.

To evaluate the accuracy of the original sizing chart, decision trees, and the multinomial regression model, confusion matrices were generated. These matrices compared the preferred sizes identified during the trials with the sizes recommended by each model, providing a quantitative measure of prediction performance. While the analysis could be extended to provide separate recommendations for the jacket and trousers, only an overall bomb suit size will be discussed here.

Figure 2. Fitting exercise of the bomb suit

Figure 3. The leg expander sizing feature from the bomb suit, worn on both legs, adds 10 cm to the circumference of each leg

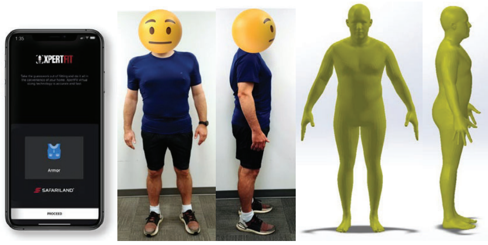

Figure 4. Photos and corresponding avatars from the XpertFit Android application

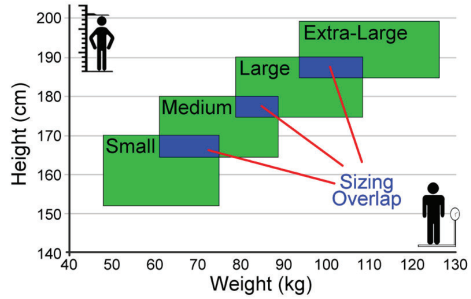

Figure 5. Original sizing chart for the bomb suit as provided by the manufacturer

3. RESULTS

The best-fitting options (preferences) identified by the 177 volunteers are presented in Figure 6, categorized by suit size selection and the use of leg expanders. The "X" marks on the graph denote cases where volunteers could not properly don any suit, based on evaluations by a bomb suit sizing expert. The suit size preferences shown in Figure 6 were compared to the original sizing chart provided by the manufacturer (Figure 5) to evaluate the chart's effectiveness in predicting the best fit. These comparisons are summarized in Figure 7 using a confusion matrix. The matrix displays the actual best-fit results across each row and the manufacturer's sizing chart predictions across each column. Green cells represent correct predictions by the sizing chart, while pink cells indicate incorrect predictions.

Performance metrics are provided for additional clarity. The percentages listed in the last column of the confusion matrix represent "recall," which reflects the proportion of volunteers correctly classified for each size. For example, only 63% of the Small volunteers were correctly classified (24 correct classifications out of 38 total Small volunteers: 24+4+10). Similarly, the percentages in the last row indicate "precision," representing the accuracy of the sizing chart's predictions. For instance, 69% of the predictions for Extra-Large were correct (9 accurate predictions out of 13 total predictions: 4+9).

The overall performance of the sizing chart was 68%, as indicated in the bottom-right corner of the matrix. This value was calculated by dividing the total number of correct predictions (green cells) by the overall number of volunteers (177).

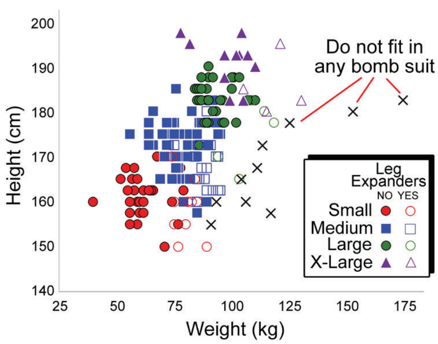

Figure 6. User preferences for suit sizes and the use of leg expanders for the 177 volunteers

ACTUAL BEST FIT \ PREDICTED - SIZING CHART	Small	Medium	Large	X-Large	No-Fit	Recall
Small	24	4			10	63%
Medium		44	14		13	62%
Large		1	34	4	4	79%
X-Large			2	9	4	60%
No-Fit					10	100
Precision	100%	90%	68%	69%	24%	68%

Figure 7. Confusion matrix: 177 users vs. the original sizing chart from the manufacturer

In the next step, the results from Figure 6 were input into the MATLAB CART algorithm to construct the most accurate decision tree for bomb suit sizing. Some pruning of the tree (removal of lower-level branches) was applied to balance performance and clarity, as shown in Figure 8. The data from each of the 177 volunteers were then passed through the tree to generate predictions. As with the evaluation of the manufacturer's sizing chart, a confusion matrix was created (Figure 9) to compare the predictions from the decision tree with the volunteers' preferences. The decision tree achieved an overall accuracy of 85%, significantly outperforming the 68% accuracy of the manufacturer's sizing chart. It is also worth noting that the precision of the "No-Fit" cases improved substantially, rising from 24% in Figure 7 (with the sizing chart) to 60% in Figure 9 (with the decision tree).

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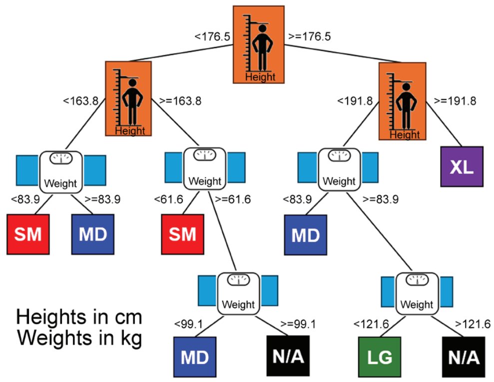

Figure 8. Decision tree for the bomb suit size generated based on height and weight only for the 177 volunteers

ACTUAL BEST FIT \ PREDICTED - DECISION TREE	Small	Medium	Large	X-Large	No-Fit	Recall
Small	32	2				94%
Medium	6	63	2		4	84%
Large		6	40	4		80%
X-Large				10		100%
No-Fit			1	1	6	75%
Precision	84%	89%	93%	67%	60%	85%

Figure 9. Confusion matrix: 177 users vs. the bomb suit size decision tree

While the manufacturer's sizing chart (Figure 5) does not include any recommendations for the use of leg expanders, a decision tree incorporating the data from the user's preferences (Figure 6) was built to provide such recommendations. Once again, the MATLAB CART algorithm was applied, and the resulting decision tree is shown on Figure 10. It must be noted that this decision tree can only be built once the decision tree for the bomb suit size has been built, since some decision steps in the leg expander decision tree depend on the suit size selected. Figure 11 then presents the confusion matrix specific to the leg expander recommendations. A relatively low recall performance was observed for the cases where users felt more comfortable with leg expanders. Indeed, in 13 cases, the decision tree failed to arrive at the same outcome. Despite this, a high overall accuracy of 90% was obtained for this decision tree.

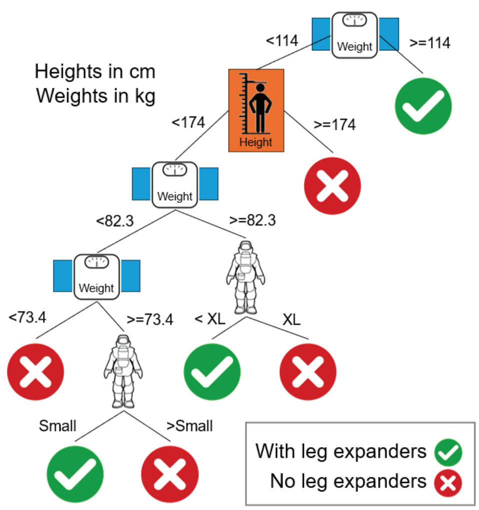

Figure 10. Decision tree for the use of leg expanders generated based on height and weight only for the 177 volunteers

Leg Expanders — ACTUAL BEST FIT \ PREDICTED DECISION TREE	No	Yes	Recall
No	124	5	96%
Yes	13	35	73%
Precision	91%	88%	90%

Figure 11. Confusion matrix: 177 users vs. the leg expanders decision tree

An improved sizing chart can be created by integrating the volunteers' preferences for bomb suit size (decision tree from Figure 8) and the use of leg expanders (decision tree from Figure 10). Figure 12 illustrates the data from all 177 individuals, plotted against the size boundaries predicted by the two decision trees. Shaded areas indicate cases where the use of leg expanders is recommended. This figure provides a clear graphical representation of the overall prediction accuracy, effectively highlighting both correct and incorrect predictions based on the placement of each data point on the chart.

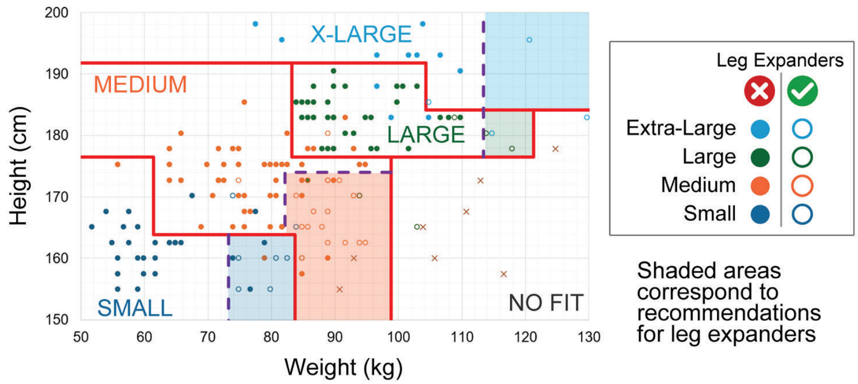

Figure 12. Sizing chart combining bomb suit size and leg expanders, derived directly from the two decision trees – individual preferred sizes displayed

The sizing chart in Figure 12 highlights a notable limitation: the area corresponding to individuals taller than 185 cm and weighing less than 75 kg (top left) contains no data points. This absence is likely due to the rarity of such individuals (very tall and slim) in the general population. Consequently, predictions for this region are unreliable and would likely fail to align with actual data, should such individuals exist. It is also doubtful that all individuals with these characteristics could properly fit into a bomb suit. Furthermore, this gap causes the sizing chart to predict a jump directly from Medium to Extra-Large for tall individuals weighing less than approximately 85 kg, bypassing the Large size entirely. Additionally, Figure 12 shows volunteers who were deemed unable to fit properly into a bomb suit by the bomb suit sizing expert (marked as "x" in Figure 12) but were incorrectly placed in the "Medium with leg expanders" area. These individuals were too large for a Medium suit yet not tall enough to fit into a Large suit. This observation indicates the need for adjustments in this area of the chart.

To overcome these shortcomings, a revised sizing chart was developed, incorporating targeted manual adjustments to address the identified weaknesses in the automatically generated version. Two key modifications were implemented: first, subtle changes were introduced to better accommodate tall, slim individuals as well as shorter, broader individuals; second, boundary lines were simplified to enhance clarity and readability. Notably, these adjustments were applied to sizing regions with minimal or no collected data points. The refined chart, shown in Figure 13, excludes the explicit display of the 177 individual data points for improved visual simplicity.

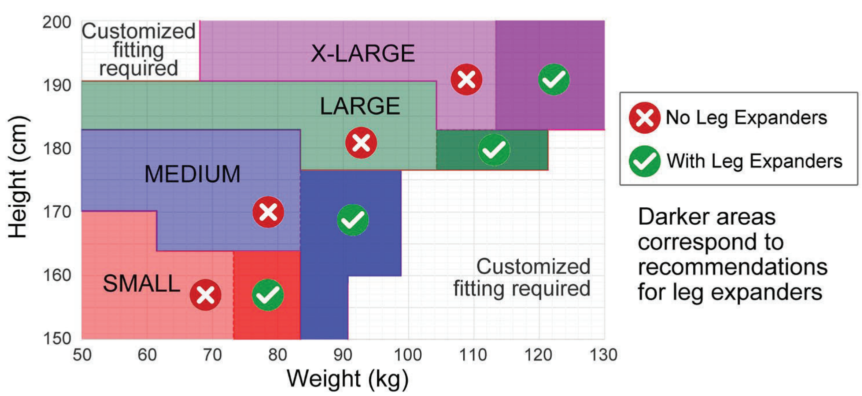

Figure 13. Sizing chart, revised and simplified to introduce regions requiring customized user fitting

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But while the revised sizing chart (Figure 13) is much more effective at predicting bomb suit size, while at the same time offering recommendations for the usage of leg expanders, it must be kept in mind that it only takes height or weight of individuals into consideration. As other body measurements can play a major role in determining sizing, a different approach incorporating the 83 measurements provided by the XpertFit app was then followed. A machine learning algorithm, proposed by Dionne [7] was applied to the entire data set. This algorithm consisted in considering five binary linear logistic regressions, each corresponding to a specific bomb suit size (including the "No Fit" case). These five equations are respectively used to answer the following five questions:

- Is the individual more likely to be size SMALL than any other size?
- Is the individual more likely to be size MEDIUM than any other size?
- Is the individual more likely to be size LARGE than any other size?
- Is the individual more likely to be size X-LARGE than any other size?
- Is the individual more likely to not fit into any bomb suit, as opposed to be able to fit?

In each case, a linear equation (Equation 1) is generated by associating a multiplying factor to each of the 83 body measurements from the XpertFit app:

$$F = f_0 + f_1 \cdot x_1 + f_2 \cdot x_2 + (\ldots) + f_{83} \cdot x_{83} \quad \ldots \qquad \ldots\ldots\ldots\ldots(1)$$

where each x corresponds to the value of a body measurement, and each f is a multiplying factor. Such a linear equation is built for each of the five cases highlighted above. The various factors are then optimized to offer the best possible accuracy in size predictions, when compared with the preferences from the 177 individuals. A sigmoid function (Equation 2) is then applied to the results of the five linear equations:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \qquad (2)$$

This sigmoid function results in a value between 0 and 1. When the value is below a threshold of 0.5, it is generally considered that the statement is true, otherwise it is considered as false. But for this specific problem, the highest value from the five sigmoid functions was sought. The size corresponding to this highest value was then considered as the most likely size for the individual.

Size predictions were generated using the machine learning algorithm for all 177 individuals, and the results were compared to their preferred sizes in the form of a confusion matrix (Figure 14). This approach achieved an overall accuracy of 92%, outperforming the decision tree method, which had an accuracy of 85% (Figure 9). Notably, both the recall and precision for the "No Fit" case reached a perfect 100%, a significant improvement over the decision tree approach, which achieved recall and precision values of 75% and 60%, respectively.

The same machine learning algorithm proposed by Dionne [7], utilizing Equations 1 and 2, was also applied to predict whether volunteers required the use of leg expanders. This analysis produced another confusion matrix (Figure 15), with an overall accuracy of 92%. This is slightly higher than the 90% accuracy obtained using the CART decision tree.

ACTUAL BEST FIT	PREDICTED - XPERT FIT: Small	Medium	Large	X-Large	No-Fit	Recall
Small	37	1				97%
Medium		67	4			94%
Large		4	38	1		88%
X-Large			4	11		73%
No-Fit					10	100
Precision	100%	93%	83%	92%	100%	92%

Figure 14. Confusion matrix: 177 users vs. the bomb suit size Multinomial Linear Regression based on the XpertFit data

Leg Expanders (ACTUAL BEST FIT)	PREDICTED MULTINOMIAL REG: No	Yes	Recall
No	130	6	96%
Yes	9	31	78%
Precision	94%	84%	92%

Figure 15. Confusion matrix: 177 users vs. the Leg Expanders Multinomial Linear Regression based on the XpertFit data

4. DISCUSSION

This study was initiated in response to some issues observed with the existing manufacturer's sizing chart for the bomb suit ensemble, with the goal of improving sizing recommendations. The original sizing chart (Figure 5) was developed without extensive trials involving volunteers, relying instead on approximations and common sense. Additionally, the original chart included overlapping areas, which caused confusion among end users whose height and weight fell within these ambiguous zones.

The experimental bomb suit fitting trials involving 177 volunteers confirmed that the legacy sizing chart could be improved (accuracy of 68%). Using the height and weight of the volunteers, along with their known size preferences, a decision tree model was developed, resulting in a significantly improved sizing chart with an accuracy of 85% (Figure 13). Unlike the legacy chart, this new sizing chart also provided recommendations on the use of leg expanders. Furthermore, a machine learning approach based on multiple linear logistic regressions achieved an even higher overall accuracy of 92% for both suit size and leg expander recommendations. These results are summarized in Figure 16.

Based on these findings, the logistic regression approach appears to be the most accurate and should be prioritized. However, the decision tree approach remains valuable due to its simplicity and usability. The decision tree allows for a clear graphical representation, enabling end users to quickly determine their recommended size—a practical feature for inclusion in product specifications. In contrast, the logistic regression model, which relies on 83 body measurements, does not lend itself to the creation of a simple sizing chart. Moreover, access to the XpertFit app is required to generate these measurements, a tool that may not be available to all users. By contrast, height and weight remain the most accessible and universally known measurements, making the decision tree approach highly practical despite its slightly lower accuracy. Both approaches are therefore valuable.

This study focused on the bomb suit ensemble as a whole (jacket and trousers), but the same methodology could be applied to provide separate sizing recommendations for jackets and trousers. This could enable "mix-and-match" sizing for individuals, a direction that warrants exploration in future research. In the case of decision trees, variables other than height and weight could be selected.

The accuracies reported in this study for both the decision tree and multinomial regression approaches could be further improved with a larger sample size of volunteers. Machine learning models generally benefit from larger datasets, and increasing the number of participants beyond the 177 considered here could enhance the predictive performance. Additionally, this study used static body measurements, including height, weight, and other parameters calculated through the XpertFit app. Future research could incorporate "dynamic anthropometry," as suggested by Avadenei et al. [8], by analysing volunteers' movements and conducting representative motions during the fitting process.

Finally, it is important to emphasize that this study focused on fitting individuals to pre-existing, predefined bomb suit sizes. For the development of future bomb suits, a more advanced approach can be adopted from the outset, following the Sustainable Product Evaluation, Engineering, and Design (SPEED) process described by Robinette et al. [9]. This approach will incorporate iterative sizing loops throughout the design process. Additionally, unsupervised learning techniques will be employed to better define user groups and establish optimal sizing categories for future bomb suits.

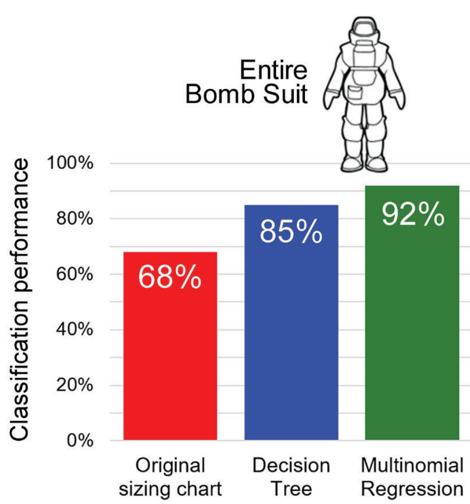

Figure 16. Comparison of the overall classification performance for the entire bomb suit for the three cases considered: original sizing chart, decision tree, and multinomial regression

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5. CONCLUSION

This study demonstrated that bomb suit sizing accuracy can be significantly improved through data-driven approaches. The original sizing chart, while useful, achieved limited predictive performance. By applying a decision tree based on height and weight, accuracy improved substantially. A further enhancement was achieved using a machine learning model incorporating detailed anthropometric data, resulting in a 92% success rate for both suit size and leg expander recommendations. These findings suggest that integrating advanced modelling techniques into PPE size selection can enhance both fit and user satisfaction. While the decision tree offers a practical and accessible solution for most users, the machine learning approach provides the greatest accuracy and should be adopted where feasible. Future efforts should focus on larger datasets and dynamic anthropometry to further refine these models and support the development of next-generation bomb suits.

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