



# BEYOND ONE-SIZE-FITS-ALL: A MACHINE LEARNING APPROACH TO CLASSIFYING FIRE DEPARTMENT PHYSICAL FITNESS NEEDS Joel Martin<sup>1</sup>, Mark Abel<sup>2</sup>, Megan Sax van der Weyden<sup>1</sup>, Mike Toczko<sup>1</sup>, Marcie Fyock-Martin<sup>1</sup>, Nicholas C. Clark<sup>3</sup>

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## Introduction

Firefighters perform physically demanding tasks under extreme conditions, yet many exhibit suboptimal levels of physical fitness. This deficiency leads to diminished performance in occupational tasks and increased health risks. Research indicates that physical fitness among firefighters is heterogeneous, and personalized training programs are more effective than generic ones. Consequently, a shift away from the 'one-size-fits-all' approach is essential. Many fire departments incorporate annual physical fitness assessments into their health and wellness programs. The efficacy of these programs can be enhanced by acknowledging individual variations in physical fitness levels across the department. To support practitioners in efficiently identifying subgroups within fire departments, machine learning algorithms offer a promising solution.

## Purpose

### The purposes of the study were to:

1. Utilize an unsupervised machine learning technique to identify distinct subgroups among firefighters.

2. Examine the differences in physical fitness levels and demographic characteristics between the identified subgroups.

#### Methods

- 1406 firefighters' physical fitness records within a single fire department were analyzed.
- Physical fitness measures included body fat percentage (BF%), muscular fitness (maximum pull-up, sit-up, and push-up repetitions) and estimated aerobic capacity (VO2max) via a 3-minute step test.
- K-means cluster (KMC) analysis was used to identify subgroups of firefighters based on physical fitness measures. The number of KMCs was determined visually using the elbow method.
- Analysis of variances and chi-square tests were conducted to assess differences between the groups identified from the KMC analysis.
- Statistical significance was set to p < 0.05.

The KMC analysis identified 4 groups (e.g., clusters) of firefighters (Table 1). As expected, there were significant differences (p<0.001) in PF measures between the 4 groups.

Significant differences (p<0.001) in age, years of service, and sex distribution were observed between groups.

• Thus, ML algorithms provide a means to unbiasedly assess the existence of subgroups and determine the composition of each group, thereby offering a datadriven approach for optimizing the targeting of physical fitness interventions to specific subgroups and individuals.

By leveraging ML, fire departments can employ new approaches to enhance the delivery of their PF initiatives, ultimately supporting the occupational preparedness, health, and wellness of their firefighters.

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## Results

One group (Cluster 4) scored higher than all other groups on PF tests, except for estimated VO2max (Cluster 1>Cluster 4).

Another group (Cluster 2) had the lowest scores on all muscular PF tests and the highest BF%.

# Conclusion

• KMC analyses revealed distinct subgroups among firefighters, providing insight into the heterogeneous nature of firefighter physical fitness within one department Significant differences (p<0.001) in age, years of service, and sex distribution were observed between groups.

Generally, the groups consisted of 1) younger, fitter 2) young, less fit, 3) older, fitter and 4) older, fitter firefighters.

• Notably, while group-level differences in age and sex were evident, individual-level data revealed that females and older firefighters may belong to more 'fit' subgroups

# Practical Applications

## Table

Variable Age (years)

**Years of service** Sex

Height (m) Mass (kg) BMI (kg/m2) **Pull-ups (reps)** Sit-ups (reps) Push-ups (reps) Relative VO<sub>2</sub>ma Absolute VO<sub>2</sub>m Body Fat (%)



Notes: Table values are presented as mean (standard deviation) for continuous and %(n) for categorical variables. Abbreviations: reps, repetitions. Partial eta-square effect sizes were categorized as trivial ( $\eta 2 = 0.01 +$ ), medium ( $\eta 2 = 0.06 +$ ), and large ( $\eta$ 2=0.14+). For significant main effects, Tukey post-hoc contrasts were performed with single step adjusted p-value. Black line on relative VO2max indicates NFPA recommendation of 42.0 mL/kg-min for VO2max of firefighters

1: Comparison of demographics and health-related component of physical fitness measures									
	Overall (n=1406)	Cluster 1 (n=239)	Cluster 2 (n=326)	Cluster 3 (n=424)	Cluster 4 (n=417)	p-value	Effect Size	Post-hoc comparisons	
	37.4(10.1)	42.8(9.5)	43.3(9.3)	35.5(9.1)	31.6(7.6)	< 0.001	Large	1>3, 1>4, 2>3, 2>4, 3>4	
(years)	10.7(8.8)	14.8(8.8)	15.5(8.4)	8.8(7.8)	5.4(6.4)	< 0.001	Large	1>3, 1>4, 2>3, 2>4, 3>4	
Males	90.2% (1268)	99.5% (238)	76.3% (249)	87.0% (369)	98.8% (412)	< 0.001	N/A	2 vs. 1, 3 vs. 1, 3 vs. 2, 4 vs. 2, 4 vs. 1	
Females	9.8% (138)	0.4% (1)	23.6% (77)	13.0% (55)	1.2% (5)				
	1.73 (0.13)	1.75(0.14)	1.73(0.13)	1.72(0.13)	1.72(0.13)	0.104	Trivial	N/A	
	91.5(15.9)	92.1(12.4)	99.9(18.6)	91.3(16.1)	84.9(11.5)	< 0.001	Medium	2>1, 1>4, 2>3, 2>4, 3>4	
	31.0(6.2)	30.6(5.5)	33.5(6.1)	31.2(6.5)	29.0(5.7)	< 0.001	Medium	2>1, 1>4, 2>3, 2>4, 3>4	
	6.1(5.0)	5.7(3.2)	0.9(1.5)	4.8(3.1)	11.8(3.4)	< 0.001	Large	All clusters sig. different	
	43.9(8.2)	41.5(5.7)	35.3(7.3)	45.9(5.1)	49.9(6.1)	< 0.001	Large	All clusters sig. different	
	38.3(12.8)	38.2(7.7)	24.0(9.4)	36.9(8.0)	50.8(8.1)	< 0.001	Large	1>2, 4>1, 3>2, 4>2, 4>3	
x (mL/kg-min)	45.4(6.6)	54.1(5.3)	42.3(5.3)	41.8(3.9)	46.6(5.2)	< 0.001	Large	1>2, 1>3, 1>4, 4>2, 4>3	
ax (L/min)	4.2(0.9)	5.0(0.8)	4.3(1.1)	3.8(0.8)	4.0(0.7)	< 0.001	Large	1>4, 2>4, 4>3, 1>3, 2>3	
	23.3(7.6)	22.1(5.5)	31.6(5.7)	24.4(5.2)	16.3(4.7)	< 0.001	Large	All clusters sig. different	

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### Figure 1: Cluster distribution comparisons of health-related components of physical fitness measures