

Allostatic Load in Firefighter Recruits: Weekly Physiological Stress Trends

and Load Management Implications

Joel Martin^{1,2}, Abdul Hafeez³, Sanja Avramovic³, Shane Caswell¹

¹ Sports Medicine Assessment, Research & Testing (SMART) Laboratory, George Mason University, Manassas, VA, USA;

² Center for the Advancement of Well-Being, George Mason University, Fairfax, VA, USA; ³ Department of Health Administration and Policy, George Mason University, Fairfax, VA, USA



Introduction

Becoming a professional firefighter requires recruits to complete a physically and mentally demanding fire academy, which imposes a high allostatic load (AL). This warrants examination of physiological measures of cumulative stress and adaptation to mitigate health-related issues of firefighter recruits. Measures such as resting heart rate, blood pressure, and bodyweight are known to be impacted by chronic stress. Previous studies provide limited insight, as AL measures are typically reported only at the start and end of fire academies.

Purpose

To examine the weekly dynamics of physiological indicators of allostatic load (AL) over a 6-month fire academy.

Methods

- Data from two 30-week FA classes ($n = 34$ recruits; 17 per class) were analyzed.
- Class A completed EMT training before FF training, while Class B completed FF training before EMT training.
- FF recruits had daily morning measurements taken in a rested state: body weight (BW), resting heart rate (RHR), respiratory rate (RR), systolic and diastolic blood pressure (BP), and self-reported stress (SRS) levels.
- For each recruit, weekly averages were computed, and changes in measures were assessed for FIRE training, EMT training, and the entire FA using t-tests.
- Linear mixed-effects (LME) models were used to evaluate weekly changes, with week as a fixed effect and random intercepts to account for individual differences and repeated measures. The model fit was assessed using the AIC and BIC. The intra-class correlation coefficient (ICC) was computed to determine the proportion of variance due to individual differences.
- To further assess overall trends, linear and non-linear growth models (1st order quadratic and cubic spline) were computed. Likelihood ratio tests were conducted to determine whether nonlinear models provided a significantly better fit than linear models.

Results

- At baseline, the only significant difference between classes was systolic blood pressure (Class A > Class B; $t(26.96) = 2.283, p = 0.031$).
- Over the entire FA, Class A experienced a significant increase in diastolic BP ($p = 0.038, d = 0.61$), whereas Class B showed no significant ($p > 0.05$) overall changes in AL markers. However, LME models revealed that week significantly influenced multiple AL measures, indicating fluctuations in stress responses throughout the academy.
- For Class A, the LME model was found to have a significant effect of week on BW ($F = 1.943, p = 0.004, ICC = 0.99$), Urine ($F = 4.101, p < 0.001, ICC = 0.73$), RHR ($F = 1.755, p = 0.012, ICC = 0.71$), RR ($F = 1.807, p = 0.009, ICC = 0.55$), self-report stress ($F = 4.160, p < 0.001, ICC = 0.56$), systolic BP ($F = 5.130, p < 0.001, ICC = 0.53$) and diastolic BP ($F = 2.719, p < 0.001, ICC = 0.56$).
- For Class B, the LME indicated a significant effect of week on BW ($F = 3.235, p < 0.001, ICC = 0.99$), Urine ($F = 1.543, p = 0.040, ICC = 0.74$), self-report stress ($F = 3.716, p < 0.001, ICC = 0.44$), systolic BP ($F = 2.112, p < 0.001, ICC = 0.70$) and diastolic BP ($F = 2.570, p < 0.001, ICC = 0.64$).
- Further modeling analyses demonstrated that nonlinear models provided a better fit for AL dynamics than linear models, particularly for body weight, RHR, systolic BP, and diastolic BP. Specifically, cubic spline models significantly improved model fit over linear models for RHR ($p = 0.033$), systolic BP ($p = 0.045$), and diastolic BP ($p = 0.047$), suggesting complex physiological adaptation patterns rather than a simple linear declines.

Conclusion

While few overall changes in AL were observed from the start to end of the FA, weekly fluctuations highlight the impact of training demands and individual variability on physiological stress responses. The nonlinear nature of the responses highlight complex physiological adaptations occurring throughout the FA.

Practical Applications

Strength and conditioning professionals should consider implementing load management strategies to balance training stress and build resilience in FF recruits. Continuous AL monitoring can help identify recruits at risk for heightened stress, enabling proactive adjustments in training and recovery.

Main Findings

- While overall changes in stress biomarkers from the start to end of the academy were minimal, week-to-week fluctuations and non-linear trends emerged, highlighting the complex nature of firefighter recruits' adaptations to training.
- Individual variability plays a significant role in shaping stress responses throughout a fire academy.
- Physical fitness showed some influence on stress responses associate with allostatic load during more physically demanding periods, suggesting that fitness levels can modulate stress to some extent.

Table 1: Fire Academy Class A Modeling Results

Bodyweight					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	<0.001	0.989	0.381	2114	2139
Quadratic	0.0005	0.990	0.380	2093	2122
Cubic	0.001	0.978	<0.001	2092	2126
Quadratic fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than linear ($p < 0.001$)					
No difference between quadratic and spline ($p = 0.115$)					
Resting Heart Rate					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.012	0.713	0.009	2707	2732
Quadratic	0.014	0.697	0.009	2707	2736
Cubic	0.016	0.718	<0.001	2704	2737
No difference between linear and quadratic ($p = 0.143$)					
Cubic spline fits data better than linear ($p = 0.033$)					
Cubic spline fits data better than quadratic ($p = 0.031$)					
Respiratory Rate					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.011	0.557	0.039	1499	1524
Quadratic	0.022	0.569	0.039	1489	1519
Cubic	0.023	0.568	0.031	1490	1524
Quadratic fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than linear ($p = 0.002$)					
No difference between quadratic and cubic spline ($p = 0.231$)					
Self-reported Stress					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.003	0.516	0.239	1103	1128
Quadratic	0.038	0.554	0.235	1070	1099
Cubic	0.039	0.556	0.002	1070	1103
Quadratic fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than linear ($p = 0.002$)					
No difference between quadratic and cubic spline ($p = 0.211$)					
Systolic BP					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.002	0.483	0.378	2858	2883
Quadratic	0.066	0.544	0.381	2799	2828
Cubic	0.067	0.562	0.023	2797	2830
Quadratic fits data better than linear ($p < 0.001$)					
Spline fits data better than linear ($p < 0.001$)					
Spline fits data better than quadratic ($p = 0.045$)					
Diastolic BP					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.005	0.544	0.156	2875	2900
Quadratic	0.006	0.545	0.156	2875	2904
Cubic	0.010	0.549	0.116	2873	2907
No difference between linear and quadratic ($p = 0.216$)					
No difference between linear and cubic spline ($p = 0.065$)					
Cubic spline fits data better than quadratic ($p = 0.047$)					

Table 2: Fire Academy Class B Modeling Results

Bodyweight					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	<0.001	0.992	0.305	2282	2307
Quadratic	0.001	0.993	0.305	2233	2262
Cubic	0.002	0.994	0.203	2205	2239
Quadratic fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than quadratic ($p < 0.001$)					
Resting Heart Rate					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	<0.001	0.732	0.657	2859	2885
Quadratic	<0.001	0.732	0.657	2862	2891
Cubic	<0.001	0.732	0.807	2864	2897
No difference between quadratic and linear ($p = 0.818$)					
No difference between cubic spline and linear ($p = 0.940$)					
No difference between quadratic and cubic spline ($p = 0.791$)					
Respiratory Rate					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.002	0.734	0.462	1840	1865
Quadratic	0.002	0.734	0.462	1842	1871
Cubic	0.003	0.735	0.969	1842	1876
No difference between quadratic and linear ($p = 0.994$)					
No difference between cubic spline and linear ($p = 0.416$)					
No difference between quadratic and cubic spline ($p = 0.186$)					
Self-reported Stress					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.052	0.581	0.025	1186	1211
Quadratic	0.058	0.588	0.025	1182	1211
Cubic	0.063	0.593	0.001	1178	1211
Quadratic fits data better than linear ($p = 0.011$)					
Cubic spline fits data better than linear ($p = 0.002$)					
Cubic spline fits data better than quadratic ($p = 0.015$)					
Systolic BP					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.003	0.734	0.392	2731	2756
Quadratic	0.010	0.741	0.392	2720	2750
Cubic	0.013	0.744	0.757	2716	2750
Quadratic fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than quadratic ($p = 0.013$)					
Diastolic BP					
Model	Marginal R ²	Conditional R ²	p value	AIC	BIC
Linear	0.009	0.667	0.139	2810	2835
Quadratic	0.015	0.674	0.144	2803	2832
Cubic	0.022	0.681	0.132	2794	2828
Quadratic fits data better than linear ($p = 0.003$)					
Cubic spline fits data better than linear ($p < 0.001$)					
Cubic spline fits data better than quadratic ($p = 0.001$)					

Notes: The p-value is for fixed effect of week. Marginal R²: This value tells you how much variance is explained by the fixed effects. Conditional R²: This includes variance explained by both fixed and random effects, giving the total variance explained by the model. The likelihood ratio test was used to compare two nested models to determine if the more complex model provides a significantly better fit to the data than the simpler model. For each model the goodness of fit was evaluated with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Lower AIC and BIC values are preferred and indicate a better model in terms of fit and complexity (less complex are preferred).