Case Report

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Association between 1-mile run times in training and selected predictors: A case study

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Abstract

Runners have an interest in what variables might help them achieve faster run times. In this case study of an individual runner, six predictors are compared to his 1-mile run times over a 1-year period. The six predictors consisted of run sessions (1, 2, etc), outdoor temperature, outdoor humidity, time of day that run began, resting heart rate (HR) on day of run, and heart rate variability also on day of run. Predictors that showed statistically significant correlations were included in multiple linear regression to compare relative strength of association with run times. Two predictors qualified for regression analysis: run session and HR. Both continued to show statistically significant associations in regression.

Keywords: Running, Heart rate, Weather

INTRODUCTION

Many runners are interested in getting faster over time as they train. In the process they might also wonder what factors could be helping them achieve this goal. In this case report, 1-mile run times (51 observations) are compared to six predictors that included number of run sessions and resting heart rate. The expectation for number of run sessions is, of course that run times become faster over time. The expectation for HR is that it will decrease over time since it tends to be lower in persons who exercise compared to those who are more sedentary [1].

By convention, research and statistical analysis is reserved for group level studies rather than at the level of the individual as this study does. However, if statistical assumptions are satisfied, why not also apply these research methods to the individual? Only one previous study was located where statistical analysis was done at the level of the individual runner [2].

The purpose of the study is to: a) provide an example of how runners can study their run times in the context of predictors they might be interested in, and b) assess the strength of association between predictors in this study and run times.

CASE REPORT

The author is also the runner in this study and is now referred to as “the runner” in the paper. He also analyzed the data and wrote the paper. The runner ran the same 1-mile hilly route in his neighborhood on 51 different days over a 1-year period (4-1-19 to 4-1-20), about once per week.

Additional training for the runner during the 1-year period included distance running (about one session of 4 miles per week); interval training 3-4 times per week beginning 4-23-19 (400 meter track repeats, Fartleck, and hill repeats); and strength training 3-4 times per week (bridges, donkey kicks, and lunges). Some of the training was done with the local Fleet Feet training group [3] and some in the runner’s neighborhood and home.

Run time was the dependent variable and was compared to six independent variables (predictors):

1. Run sessions, first one = 1, second one = 2 and so on

2. Outdoor temperature, obtained from measurements taken at a local airport approximately 5 miles from the runner's neighborhood and reported on a weather website [4]

3. Outdoor humidity, also obtained from the weather website [4]

4. Time of day that run began, between 5:45 AM and 6:00 PM

5. Resting heart rate. Lower numbers are considered healthier than higher numbers

6. Heart rate variability. Higher numbers are considered healthier than lower numbers

Resting heart rate (HR) and resting heart rate variability (HRV) were self-measured by the runner in the supine position early in the morning before getting out of bed on the day of the run. Both measures (HR and HRV) were recorded simultaneously for 1-minute using the Heart Rate Variability Logger app [5] in conjunction with the Kyto ear clip sensor (6). The sensor sends a Bluetooth signal to a smartphone app and the set-up has good agreement with standard ECG technology [6,7]. For HRV, the time domain measure of root mean square of successive differences between heart beats (rMSSD), measured in milliseconds (ms) was used. The terms *rMSSD* and *HRV* are used interchangeably in this paper. HR was measured in beats per minute (BPM).

Analysis consisted of:

a) Correlation between run sessions and predictors. A negative correlation indicates an inverse relationship, e.g., run time numbers getting smaller (faster) while predictor numbers get larger (e.g., run session numbers). A positive correlation (no minus sign on the correlation coefficient) indicates a direct relationship, e.g., run times getting smaller (faster) and temperature numbers also getting smaller (cooler outside). Correlation coefficients are denoted with the small letter "r" and can have different strengths:

   - Weak (e.g., r = 0.100 or -0.100)
   - Medium (e.g., r = 0.400 or -0.400)
   - Strong (e.g., r = 0.700 or -0.700)
   - Perfect (r = 1 or -1).

b) Multiple linear regression, which determines: a) which predictors have the stronger relationship with run times and b) how much change in run time can be expected with a change in a predictor. Only predictors that showed a statistically significant correlation with run times were considered appropriate for regression.

Statistical assumptions

Linearity was determined by statistically significant correlations that had at least a medium strength. Data normality can be assumed with 30 observations or more [8]. This study had 51 observations, so the normality requirement is satisfied. Multicollinearity among predictors in multiple linear regression was assessed with the variance inflation factor (VIF). A VIF < 4.0 was considered acceptable.

Data were analyzed in Stata 12.1 (StataCorp, College Station, Texas). A two-tailed p-value < the conventional alpha level of 0.05 was considered statistically significant. A statistically significant p-value means that the result is probably due to something other than chance.

Hypotheses

The null hypothesis was that there would not be a statistically significant relationship between any predictor and run times. The alternative hypothesis was that there would be at least one predictor showing a statistically significant relationship.

RESULTS

Overview

Descriptive statistics are provided in Table 1, correlations in Table 2, and regression results in Table 3. Run times got faster in general over time, from a high of 9:08 early on to a low of 6:54 at the end (Figure 1).

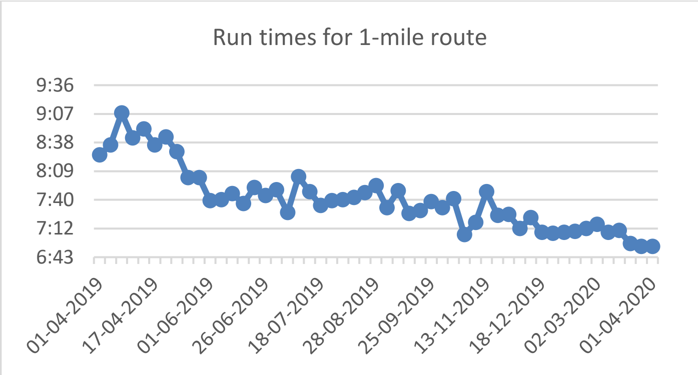

Figure 1: 1-mile run times over a 1-year period

Correlations

Two predictors showed statistically significant correlations with run times. Run session showed a strong, inverse and statistically significant correlation with run time: r = -0.881, p < 0.0001 (Table 2). The inverse correlation means that as run sessions increased, from 1 to 2, then 2 to 3 and so on, run times tended to decrease (Figure 1). HR showed a medium strength, direct, and statistically significant correlation with run times: r = 0.634, p <0.0001 (Table 2). The direct correlation means that lower HR was correlated with lower (faster) run times (Figure 2).

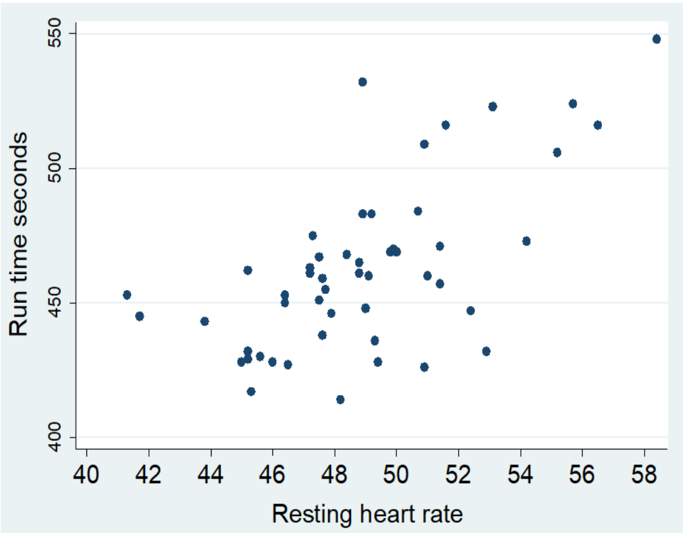

Figure 2: Scatter plot for run times versus resting heart rate

Table 1: Descriptive statistics for variables in the study

Variable	n	Mean	SD	Minimum	Maximum
Run time	51	7:41	32.0	6:54	9:08
Temperature	51	67.1	11.2	42	88
Humidity	51	60.3	20.9	24	93
Time run began	51	11:40 AM	4.5 hrs	5:45 AM	6:00 PM
Resting heart rate	51	48.9	3.5	41.3	58.4
Heart rate variability	51	37.7	10.1	20.0	63.3

n is number of observations. SD is standard deviation. Run session number was also a predictor, ranging from 1-51.

Table 2: Correlations between run time and the six predictors

Predictor	r	p
Run session	-0.881	< 0.0001
Resting heart rate	0.633	< 0.0001
Time run began	0.167	0.24
Temperature	0.194	0.17
Humidity	0.054	0.71
Heart rate variability	-0.094	0.51

r = correlation coefficient. p is the p-value.

Table 3: Multiple linear regression for run times versus the two predictors

Predictor	Coefficient	t	p	95% CI
Run session	-1.6	-9.6	<0.001	-2.0 to -1.3
Resting heart rate	1.6	2.1	0.042	0.1 to 3.1

t is t value. CI is confidence interval for the coefficient.

Regression

Both predictors that showed statistically significant correlations (run sessions and HR) continued to show statistically significant associations with run times in multiple linear regression. The model was strong: R-squared = 0.795 ($p < 0.0001$).

The predictor *run session* continued to show the stronger association with run times compared to HR evidenced by comparison of their t values. The regression coefficients were -1.6 ($t = -9.6$, $p < 0.001$) for run session and 1.6 ($t = 2.1$, $p = 0.042$) for HR (Table 3). The variance inflation factor was 1.6 for each predictor, indicating collinearity between the two predictors was not a problem.

The -1.6 coefficient for run session means that each passing run session predicts a decreased (faster) time by 1.6 seconds. A 1.6 coefficient for HR means that run time is predicted to decrease by 1.6 seconds for every 1 beat HR decrease on the day of the run.

DISCUSSION

It makes sense that more run sessions (along with the interval and strength training) would lead to, or more boldly stated, be a *cause of* the faster run times. It is less clear as to whether the low resting heart rate was an *effect*, or a *cause* of faster run times, or both.

It is well known that HR tends to be low in runners and considered as an *effect* of the running. The runner (author) has a theory that the low HR may also be a *cause* of the faster run times. A brief literature search did not reveal any scientific literature supporting this idea. The theory is plausible though. The low HR in runners is due to the greater efficiency by which the heart beats (9). Greater efficiency translates into fewer beats per minute to "get the job done." The greater efficiency in the resting state would seem transferrable to the running state, where the heart might still be able to get the job done with fewer beats. Fewer beats may then translate into less exhaustion which could translate into greater endurance (more "reserve") and therefore faster speed. Moreover, the design of this study included HR being measured *prior to* the running, further suggesting that the HR is a *causative factor* of the run times, where lower HR → lower (faster) run times; and higher HR → higher (slower) run times.

Limitations to the study include those that typically pertain to observational type studies such as this one. One of the main limitations is that these results may only pertain to this runner rather than other runners.

CONCLUSION

In this case study, run session and resting heart rate were significant predictors of the runner's run times over the 1-year study period. Further research using this case study approach in other runners is a reasonable next step.

Conflicts of Interest

The author has no conflicts of interest to declare.

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