

Introduction

Road safety remains a persistent public health issue, with more than 1.19 million fatalities annually worldwide. Within the European Union, **53% of road fatalities occur on rural roads** due to higher speeds, reduced surveillance, and lower infrastructure standards. Human factors are implicated in approximately **95% of road crashes**. However, little empirical research has explored how physical fitness shapes driving performance.

Driving is a complex psychomotor activity depending on the continuous integration of perception, attention, judgment, and motor coordination. Cardiorespiratory fitness and regular exercise are associated with **cognitive alertness, better stress regulation, and enhanced motor responses**, all of which may affect a driver's ability to anticipate hazards, maintain safe distances, and react appropriately to critical events.

This study aims to address this gap by examining the relationship between **objectively measured physical fitness** and key indicators of driving performance among young drivers in a high-fidelity simulated rural environment.

Methodology

A total of **46 young licensed drivers** aged 19 to 27 years (23 males, 23 females) participated.

Cardiorespiratory fitness was assessed using the **Queen's College Step Test**: participants stepped on a 41.3 cm platform for 3 minutes (24 steps/min for males, 22 steps/min for females). Heart rate was continuously monitored with a **Garmin HRM-Pro™ Plus** chest strap and recorded 20 s after the test to estimate $VO_2\max$:

Men: $VO_2\max = 111.33 - (0.42 \times HR)$

Women: $VO_2\max = 65.81 - (0.1847 \times HR)$

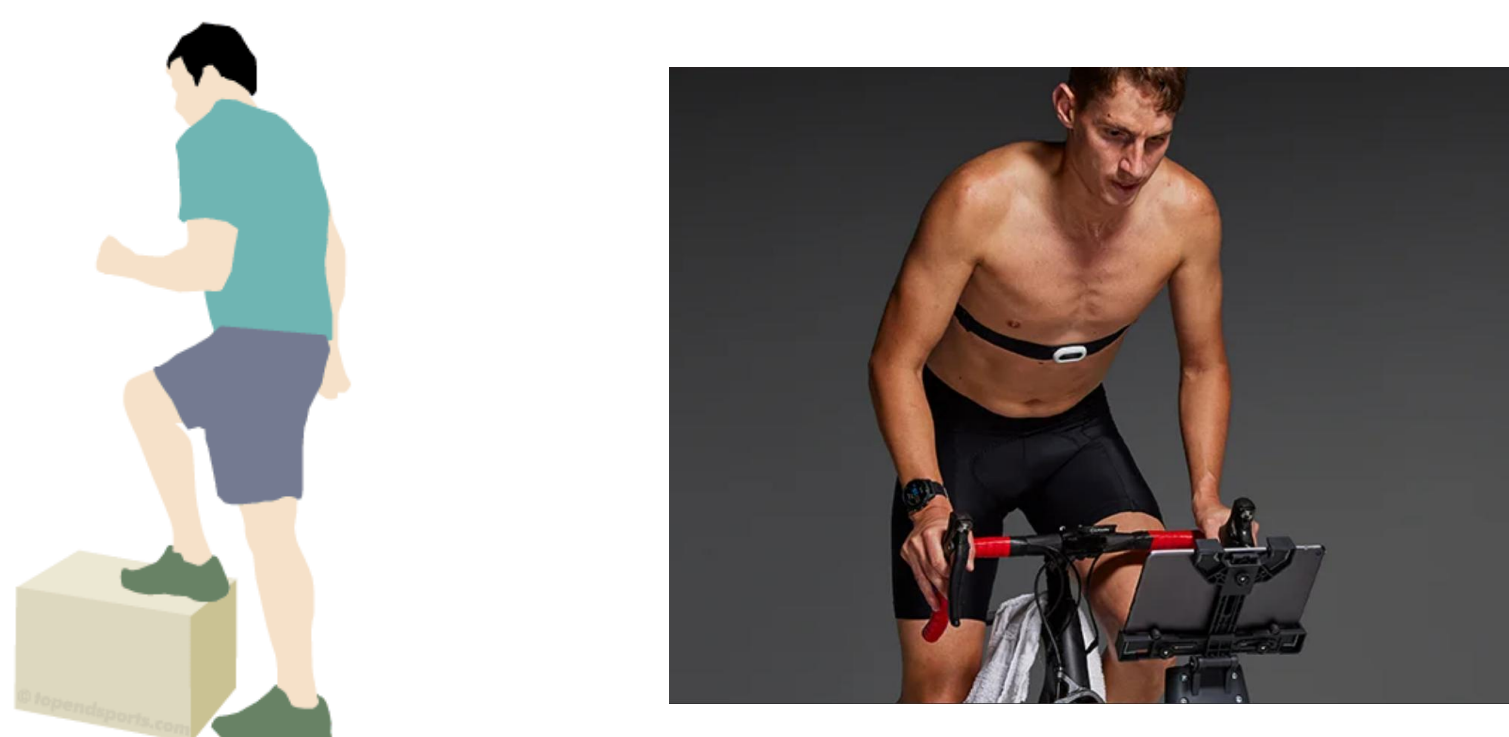


Figure 1 Queen's College Step Test (left) and heart rate monitoring with a Garmin HRM-Pro™ Plus chest strap (right)

Participants were classified into **two fitness groups** based on established $VO_2\max$ normative values: low fitness (very poor to good; 57%, N=26) and high fitness (excellent to superior; 43%, N=20).

Table 1. Normative values for maximum oxygen consumption ($VO_2\max$) by age and sex (values in ml/kg/min)

Sex	Age	Very Poor	Poor	Fair	Good	Excellent	Superior
Female	13-19	<25.0	25.0-30.9	31.0-34.9	35.0-38.9	39.0-41.9	>41.9
	20-29	<23.6	23.6-28.9	29.0-32.9	33.0-36.9	37.0-41.0	>41.0
	30-39	<22.8	22.8-26.9	27.0-31.4	31.5-35.6	35.7-40.0	>40.0
	40-49	<21.0	21.0-24.4	24.5-28.9	29.0-32.8	32.9-36.9	>36.9
	50-59	<20.2	20.2-22.7	22.8-26.9	27.0-31.4	31.5-35.7	>35.7
	60+	<17.5	17.5-20.1	20.2-24.4	24.5-30.2	30.3-31.4	>31.4
Male	13-19	<35.0	35.0-38.3	38.4-45.1	45.2-50.9	51.0-55.9	>55.9
	20-29	<33.0	33.0-36.4	36.5-42.4	42.5-46.4	46.5-52.4	>52.4
	30-39	<31.5	31.5-35.4	35.5-40.9	41.0-44.9	45.0-49.4	>49.4
	40-49	<30.2	30.2-33.5	33.6-38.9	39.0-43.7	43.8-48.0	>48.0
	50-59	<26.1	26.1-30.9	31.0-35.7	35.8-40.9	41.0-45.3	>45.3
	60+	<20.5	20.5-26.0	26.1-32.2	32.3-36.4	36.5-44.2	>44.2

Low-fitness High-fitness

A **structured questionnaire** covering driving exposure, physical activity habits, perceived effects of fitness on driving, accident history, and demographics complemented the fitness assessment.

The experimental sessions were carried out on the high-fidelity **FOERST Driving Simulation FPF** at the Traffic Engineering Laboratory, NTUA, featuring a full driver cockpit (steering wheel, pedals, gear lever) and a triple LCD monitor display system providing a wide field of view with motion across all dimensions.



Figure 2 Environment of the driving simulator

Participants completed **three standardized rural road scenarios** in random order: (i) daytime with low traffic flow, (ii) daytime with high traffic flow, and (iii) nighttime with low traffic flow. All scenarios shared the same geometric design, signage, and posted speed limits. Sudden hazard events (e.g., a deer unexpectedly crossing the road) were introduced to evaluate reaction times and hazard-avoidance behaviour.



Figure 3 Digital environment of the driving simulator: (i) daytime scenario, and (ii) unexpected hazard event.

Linear regression models were developed for continuous dependent variables (headway variability, mean reaction time, average speed). A binary logistic regression model was applied for accident probability (collision=1, avoidance=0).

Results

Four regression models were estimated to examine the association between physical fitness and driving performance. Three **linear regression models** addressed headway distance standard deviation ($R^2 = 0.633$), average reaction time ($R^2 = 0.561$), and average speed ($R^2 = 0.428$). A **binary logistic regression model** estimated accident probability (72.6% correct predictions). Elasticity (e) quantifies how responsive each outcome is to a given predictor, while relevant elasticity (e*) divides each predictor's elasticity by that of the weakest predictor, enabling direct comparison of practical influence across variables measured on different scales. Below are the detailed model results (Tables 2 & 3).

Table 2. Summary of linear regression models (B: regression coefficient; t: test statistic; e: elasticity; e*: relevant elasticity).

Average Speed Linear model				
	B	t	e	e*
Discrete variables				
Fitness group (Low or High Fitness)	2.364	2.267	0.04	-3484.28
Traffic Volume (Low and High Traffic Volume)	-5.422	-5.397	-0.10	7990.50
Weekly rural road trips	1.561	2.335	0.03	-2300.02
Differences in driving under physical fatigue	2.348	2.322	0.04	-3460.16
Driver's job requires physical activity	1.046	2.192	0.02	-1541.11
Involvement in accident with property damage only	-0.001	-6.503	-0.00001	1.00
Continuous variables				
Years of participation in sports activity	0.248	2.494	0.00004	1.00
Driver's body mass index (BMI)	0.507	3.011	0.00009	2.05
$R^2 = 0.428$				

Standard Deviation of Headway Distance Linear model				
	B	t	e	e*
Discrete variables				
Fitness group (Low or High Fitness)	24.762	2.076	0.31	2.42
Lighting conditions (Day or Night time)	141.339	10.828	1.77	13.84
Traffic Volume (Low and High Traffic Volume)	-27.851	-2.134	-0.35	-2.73
Perceived influence of physical fitness on focused driving	-23.323	-2.079	-0.29	-2.28
Weekly rural road trips	-15.793	-2.141	-0.20	-1.55
Involvement in an accident as a driver	-30.524	-2.974	-0.38	-2.99
Daily minutes of walking or cycling	10.214	2.001	0.13	1.00
Continuous variables				
Driver's weight	-0.996	-2.567	-0.00012	1.00
$R^2 = 0.633$				

Average Reaction Time Linear model				
	B	t	e	e*
Discrete variables				
Fitness group (Low or High Fitness)	0.137	1.987	0.10	1.00
Lighting conditions (Day or Night time)	0.553	7.093	0.42	4.03
Traffic Volume (Low and High Traffic Volume)	-0.357	-4.577	-0.27	-2.60
Perceived influence of physical fitness on focused driving	-0.212	-3.150	-0.16	-1.55
Weekly rural road trips	-0.149	-3.409	-0.11	-1.09
Driver's body mass index (BMI) category	0.171	2.330	0.13	1.25
Continuous variables				
Driver's weight	-0.009	-2.940	-0.00007	1.00
$R^2 = 0.561$				

Table 3. Logistic regression model (B: regression coefficient; z: test statistic; e: elasticity; e*: relevant elasticity).

Accident Probability Binary logistic model				
	B	z	e	e*
Discrete variables				
Fitness group (Low or High Fitness)	-0.933	-1.936	-0.02	2.25
Lighting conditions (Day or Night time)	1.604	3.228	0.18	-21.49
Differences in driving under physical fatigue	-1.794	-3.153	-0.01	1.78
Driver's job requires physical activity	0.849	3.256	0.09	-10.92
Type of sports activity most frequently practiced	-1.061	-2.957	-0.008	1.00
Educational level	0.724	2.038	0.09	-11.06
Annual household income	0.763	2.223	0.09	-10.69
Continuous variables				
Months of sports participation per year	0.420	4.178	1.07	1.00
Correct Predictions: 72.6%				

Key Findings

Comparative regression analyses revealed **significant behavioural differences between fitness groups**.

Compared to low-fitness drivers, **high-fitness drivers demonstrated:**

- Greater headway distance variability.
- Slightly longer reaction times.
- Higher average speeds.
- Lower accident probability.

↑ Headway Distance SD

High-fitness drivers: $\beta = +24.76$, $p < 0.05$
More dynamic spacing regulation and adaptive rather than unstable

↑ Reaction Time

High-fitness drivers: $\beta = +0.137$, $p < 0.05$
Slightly longer RT may reflect more deliberate decision-making

↑ Speed

High-fitness drivers: $\beta = +2.364$, $p < 0.05$
Higher confidence and smoother integration into traffic flow

↓ Accident Probability

High-fitness drivers: $\beta = -0.933$, $p < 0.10$
Indicating a protective effect

Furthermore, regarding **environmental impacts:**

- Nighttime conditions led to markedly greater headway variability, longer reaction times, and increased accident probability.
- Higher traffic flow reduced headway variability, shortened reaction times, and lowered average speed.

Elasticity analysis showed that **lighting conditions** had the strongest relative influence across all models, while physical fitness exerted a moderate but meaningful effect on key behavioural and safety-related outcomes.

Discussion & Conclusion

The combination of greater headway variability, slightly longer reaction times, higher speed, and lower accident probability among high-fitness drivers points to a **more dynamic yet strategically regulated driving style**. Rather than reflecting reduced control, this behavioural pattern may indicate greater readiness to adapt to changing traffic conditions and more deliberate behavioural adjustment.

Consistent with established models of speed variance and crash risk, driving slightly above the mean flow speed can facilitate smoother traffic integration. The higher speeds of high-fitness drivers likely reflect **improved readiness and control** rather than increased risk. Low visibility undermined steady spacing and timely responses, while higher traffic flow prompted a shift toward more defensive driving.

Objectively measured cardiorespiratory fitness plays a significant role in shaping key aspects of driving performance among young drivers on rural roads. The findings point to physical fitness as a **promising pathway for strengthening driver readiness** and reducing accident probability, suggesting that health-oriented interventions could complement traditional road safety strategies. Future research should validate these findings with larger, more diverse driver populations and real-world settings.

Contact Information

Marios Sekadakis

5 Iroon Polytechniou
St, Athens GR-15773,
Greece

Tel: +30 210.772.1575
Email: msekadakis@mail.ntua.gr
Web: nrso.ntua.gr/p/msekadakis/

