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Association of Sleep Quality, Screen Time, and Physical Activity with Health-Related Quality of Life among Rural and Urban Athletes: A Comparative Cross-Sectional Study

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Abstract: Sleep quality, screen time, and physical activity are modifiable behaviors linked to health-related quality of life (HRQoL) in athletes, but rural–urban comparisons among athletes remain limited. This cross-sectional study compared sleep quality, screen time, physical activity, and HRQoL between rural (n=100) and urban (n=100) athletes aged 18-30 years, and examined how these behaviors relate to HRQoL. Sleep quality, physical activity, screen time, and HRQoL were assessed with the Pittsburgh Sleep Quality Index (PSQI), International Physical Activity Questionnaire–Short Form (IPAQ-SF), Android Digital Wellbeing, and WHOQOL-BREF. Independent-samples t-tests, Pearson correlations, and multiple linear regression ($\alpha = .05$) were used. Compared with urban athletes, rural athletes reported better sleep quality (PSQI M = 4.80 vs. 6.11, d = 0.72), lower screen time (3.16 vs. 4.56 h/day, d = 1.22), higher physical activity (3,778 vs. 2,835 MET-min/week, d = 0.82), and higher HRQoL (71.01 vs. 64.70, d = 1.05; all $p < .001$). HRQoL correlated negatively with PSQI ($r = -.54$) and screen time ($r = -.53$), and positively with physical activity ($r = .42$; all $p < .001$). After adjusting for residence, age, and sex, PSQI, screen time, and physical activity remained independent predictors of the investigator-derived Global HRQoL composite (all $p < .001$), and the model explained 56.7% of variance (adjusted $R^2 = .554$); the residence effect became non-significant once these behaviors were entered. These findings suggest sleep quality, screen time, and physical activity are associated with the rural–urban HRQoL gap among athletes and may be modifiable targets for residence-sensitive lifestyle interventions, pending longitudinal confirmation.

Keywords: Health-related quality of life, Sleep quality, Screen time, Digital wellbeing, Physical activity.

1. Introduction

Health-related quality of life (HRQoL) is a multidimensional construct, including physical, psychological, social and environmental dimensions, perceived by the patient and different from the absence of disease (WHOQOL Group, 1998). In competitive sports, HRQoL is gaining recognition as a factor impacting adherence to training plans, longevity of competitive involvement, and the psychosocial adjustment after competition. Athletes have positive objective health profiles, but training load, competitive stress, sleep disturbances, and more recently problematic use of digital technology, can be detrimental to HRQoL (Vitale *et al.*, 2019). Sleep quality, physical activity, and sedentary behavior have been increasingly studied as areas that impact HRQoL more broadly and specifically in athletic populations. Sleep is essential for athletic recovery, neuromuscular function, and mood management, and poor sleep has been associated with reduced athletic recovery and decreased wellbeing in athletes (Gupta *et al.*, 2017; Walsh *et al.*, 2021), as measured through common sleep questionnaires such as the Pittsburgh Sleep Quality Index (PSQI; Buysse *et al.*, 1989). In both athletic and general populations physical activity is well correlated with improved HRQoL (Bize *et al.*, 2007; Pucci *et al.*, 2012), as quantified by the International Physical Activity Questionnaire (IPAQ; Craig *et al.*, 2003). At the same time, heavy smartphone and screen time has come to be identified as a behavioral risk factor for poor sleep, increased sedentary time, and poorer psychosocial well-being (Twenge & Campbell, 2018; Alonzo *et al.,* 2021), and more recent work in athletic samples specifically has linked smartphone and social media usage patterns to sleep disruption and mental well-being (Fiedler *et al.,* 2024; Hilpisch *et al.,* 2025), with bidirectional models suggesting technology use and sleep can each influence the other over time (Bauducco *et al.,* 2024). These behavioral–HRQoL relationships may be moderated by residential context (rural versus urban) because it can affect sports infrastructures, ambient environment, physical activity from work and transportation, digital connectivity, and lifestyle pace (Loprinzi & Cardinal, 2011). There may be more opportunities for incidental physical activity and less digital saturation in rural environments, and more opportunities for structured training facilities and more exposure to sedentary and screen time in urban environments.

HRQoL in the athlete is not a stable and a uniformly good trait, but it varies throughout the athlete's career and is influenced by the modifiable lifestyle exposures. Athletes generally reported better generic HRQoL than non-athletes, and that uninjured athletes reported better HRQoL than their injured counterparts (Houston *et al.,* 2016). Despite this apparent benefit, collegiate athletes have been found to have a poorer current HRQoL compared to non-collegiate athletes when formal athletic participation concludes (Simon & Docherty, 2014) and HRQoL and life-satisfaction have been shown to be systematically affected by a history of injury, sport type and body composition among former athletes (Filbay *et al.,* 2019). Many of the highest achieving athletes (Brauer *et al.,* 2019) report having significant problems with sleep, and problematic smartphone use is associated with increased symptoms of anxiety and depression in a wide variety of samples (Elhai *et al.,* 2017), and with higher perceived stress and lower academic performance and life satisfaction among university students (Samaha & Hawi, 2016). As per the possible pathway of sleep, higher severity of smartphone use has been directly linked to more sleep disturbances and greater depression and anxiety in university samples (Demirci *et al.,* 2015). The estimated screen-time was unbiased at the group level, and had a large amount of error from individual to individual (Hodes & Thomas, 2021), with some participants seriously over- or under-estimating their screen-time. In a Chinese adolescent and young-adult sample methodologically close to the current study's regional and cultural context, Lee *et al.,* (2021) also found a non-significant correlation between self-reported and objectively measured total smartphone usage time, and significant differences in usage time between usage domains. The results align with Ellis *et al.* (2019) and Parry *et al.* (2021) in suggesting that self-report screen-time data, despite its convenience, is unlikely to reflect device log data, which supports the methodological foundations of this study using Android Digital Wellbeing data.

One of the most widely replicated findings in behavioral epidemiology is the beneficial association between levels of physical activity and quality of life. Across all age groups and activity domains, evidence indicated that increased physical activity is correlated with increased well-being and quality of life, and these associations were seen with both self-reported and instrument-based PA measures (Marquez *et al.,* 2020). The compounded effect of noise, crowding, limited availability of green space and social fragmentation in high-density urban environments explains the observed differences, with urban residence linked to around a 40% increased risk of depression, 20% increased risk of anxiety disorders and an approximately two-fold increased risk of schizophrenia in a meta-analytic synthesis of urbanicity and psychiatric morbidity (Peen *et al.,* 2010). Yet, differences in physical activity patterns are not always as expected: nationally representative accelerometer and self-report data show that rural residents report to have more incidental (household, work, etc.) physical activity than urban residents, while urban residents may have more structured (leisure time) activity, of high intensity (Fan *et al.,* 2014). This pattern also suggests that physical activity disparities between rural and urban areas vary by domain, which is important to consider when interpreting the overall comparisons of physical activity across rural and urban areas based on the IPAQ-SF conducted in this study.

Although sleep, physical activity, screen time, and HRQoL have all been explored in separate bodies of literature, there are three specific gaps. First, most of the existing studies investigate these behavioral domains separately, instead of simultaneously as adjusted predictors of HRQoL. Second, the vast majority of screen time research in athletic and youth populations is based on self-reports, but there are reports of discrepancies between self-reported screen time and device-documented screen time (Ellis *et al.,* 2019). Third, rural–urban comparative information for competitive athletes is limited, as compared to general adolescent or adult populations, and therefore it is unclear if the residence-based differences found in the general population (Loprinzi & Cardinal, 2011) extend to athletes who are thought of as a relatively homogeneous physically active population.

2. Materials and Methods

2.1 Study Design & Population

A cross sectional, observational study done using the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) checklist for cross sectional studies (von Elm et al., 2007). Competitive athletes between 18-30 years old were selected from administrative regions in both rural and urban areas of Jammu & Kashmir. An athlete was defined as a person involved in organised competitive sports and training. Residence was classified operationally using the administrative rural/urban designation of Jammu & Kashmir (statutory towns, municipal committees/councils and notified urban agglomerations were classified as urban; all other administratively designated village/panchayat areas were classified as rural), and participants were required to have lived continuously in the classified rural or urban area for at least the preceding three years (or since birth) and to be currently training/competing while based in that area, so that residence reflected a stable rather than transient exposure.

2.2 Sample Size

A priori sample size calculation was done using power analysis software G*Power 3.1, using medium effect size (Cohen's d = 0.45) with $\alpha = .05$ and power $(1-\beta) = .80$. A target sample of N = 200 (100 rural, 100 urban) was chosen to allow for expected exclusion due to incomplete Digital Wellbeing data (~15–20%) and for the analyses, including multiple regression with six predictor variables (following Green's [1991] rule of $N \geq 50 + 8k$).

2.3 Sampling Technique

Purposive sampling with a quota method was employed. A wide selection of rural and urban areas was identified, with an emphasis placed on regions where organized sports academies/clubs and district sports associations were present. Athletes were identified from sports clubs, university/college teams and district sports federations within each region until the 100 per stratum was reached. Sex was observed to provide adequate male and female representation in each stratum (non-quota, to maintain a realistic variation).

2.4 Inclusion and Exclusion criteria

The criteria for the participants' inclusion were that they were between 18-30 years old and actively involved in organized competitive sport, having participated in at least one competitive event in the last year, and training regularly (at least 3 days a week). Individuals eligible included those who lived and represented the selected rural/urban area of interest, had written informed consent and adequate language skills in the language of the questionnaire. In addition, participants had to have an Android smartphone as their main device, and have a large amount of Digital Wellbeing usage history for at least 20 of the previous 30 days.

The participants were excluded when they had an injury that was occurring at the time which significantly restricted normal physical activity or training or if they were unable to complete the study questionnaires, either independently or with support. People with a high missing item rate of over 10% on any scale were also removed (n>10%) as were people with limited or unavailable Digital Wellbeing data. Lastly, people who relied on a phone other than Android for their main smartphone (e.g., iOS) were not included in the study, since the digital usage metrics measured are only available for Android phones.

2.5 Data Collection

Data collected is from [February – July, 2026] at selected sites in both urban and rural areas. Therapists conducted approaches with trained research assistants to eligible athletes at sports clubs, training academies, and universities sports department. Eligible participants completed a structured demographic form and the PSQI, IPAQ-SF and WHOQOL-BREF questionnaires within a single session (paper or electronic, depending on the site), with research assistant supervision to ensure minimal missing data. After finishing the questionnaire, research assistants pointed them towards their Android Digital Wellbeing dashboard on their personal devices and captured the 30-day average daily screen time. Each data collection session for each participant took about 25-35 minutes. The athletic and demographic data gathered were age, sex, sports discipline, district/state/national/international level of competition, years of training experience, and days/week of training.

2.6 Instrumentation and Outcome Scoring

Sleep quality was measured with the 19-item PSQI (Buysse *et al.,* 1989), which yields seven component scores (subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction), each rated 0–3 and summed into a global score ranging 0–21, with scores >5 indicating clinically poor sleep. Physical activity was measured with the IPAQ-SF (Craig *et al.,* 2003) and scored following the IPAQ Research Committee (2005) protocol: self-reported minutes of walking, moderate-intensity, and vigorous-intensity activity over the preceding 7 days were multiplied by their respective MET values (3.3, 4.0, and 8.0 METs) and summed to yield total MET-min/week, and participants were additionally classified into Low/Moderate/High activity categories using the standard IPAQ scoring thresholds. HRQoL was measured with the WHOQOL-BREF (WHOQOL Group, 1998; Skevington et al., 2004), which yields four domain scores (Physical Health, Psychological, Social Relationships, and Environment), each linearly transformed to a 0–100 scale following the WHOQOL scoring manual, together with two standalone items assessing overall perceived quality of life and general health that are scored separately and were not incorporated into the domain scores.

For the purposes of this study, a Global HRQoL composite was calculated a priori as the unweighted arithmetic mean of the four transformed WHOQOL-BREF domain scores (0–100 scale) for each participant. This composite is an investigator-derived summary index rather than a standard WHOQOL-BREF output, is distinct from the two standalone overall quality-of-life and general-health items, and was not itself independently validated; it was adopted a priori as the primary outcome to capture overall behaviorally relevant HRQoL rather than any single domain, and the four individual domain scores are reported alongside it (Table 2, Table 3) so that domain-specific patterns can be evaluated directly and the composite's properties judged in context. This investigator-constructed scoring is acknowledged as a limitation in the Strengths and Limitations section. The 30-day Digital Wellbeing average was obtained under research-assistant supervision: participants opened the Android Digital Wellbeing dashboard on their own device and read out the daily screen-time value for each of the preceding 30 days, which the research assistant recorded and averaged. Participants were required to have at least 20 of the preceding 30 days of available history to be included; those with fewer than 20 days of history, or with a usage pattern suggesting the device had recently been reset, replaced, or shared, were excluded prior to analysis (see Inclusion and Exclusion Criteria).

2.7 Ethical Considerations

All the participants signed informed consent forms after receiving information regarding purpose of the study, study procedure, voluntary participation, right to withdraw from the study without any penalty, and measures of confidentiality protection. Screen-time was extracted in a transparent manner and the participant viewed and controlled their device, no third-party access to devices was allowed, and no personally identifying information was kept in the analytic dataset.

2.8 Statistical Analysis

Data analysis was done using SPSS v.28. Demographic, athletic and study variables were characterized using descriptive statistics (means, standard deviations, frequencies and percentages) (Table 1, Table 2). Normality was checked using Shapiro–Wilk tests and by inspection of Q–Q plots with continuous variables, parametric analysis was used with these variables as they are thought to approximate normal distributions. Independent-samples t-tests (Welch's correction, if Levene's test was significant), were used to compare the groups (rural vs urban) on PSQI, screen time, MET-min/week and WHOQOL-BREF domain/global scores, with Cohen's d reported as the effect size (Table 3). Bivariate associations between PSQI, screen time, MET-min/week and HRQoL were explored using Pearson product-moment correlations (Table 4). All independent associations while controlling for demographic and residential covariates were examined by multiple linear regression models, with HRQoL global score as the dependent variable and PSQI, screen time, MET-min/week, residence (rural = 0, urban = 1), age and sex (female = 0, male = 1) as independent predictors (Table 5). For all model variables, variance inflation factors (VIF) were computed to check for multicollinearity, with VIF values of less than 2 for all of them; multicollinearity diagnostics assess redundancy among predictors and are conceptually distinct from scale reliability, which was instead evaluated using published internal-consistency estimates for the PSQI, IPAQ-SF and WHOQOL-BREF from their respective validation studies, since item-level responses were not retained for post-hoc Cronbach's alpha calculation in this dataset. Regression assumptions were further assessed by visual inspection of standardized residual histograms and P–P plots for approximate normality, a residuals-versus-fitted-values plot for linearity and homoscedasticity, and Cook's distance for influential cases (maximum Cook's D < 1 for all cases, indicating no disproportionately influential observations); no material violations of these assumptions were observed. A level of 0.05 (2-tailed) was used for determining statistical significance. The distribution of sport discipline (team versus individual) across residence strata was compared using a chi-square test of independence with Yates' continuity correction, and the strength of association was quantified using Cramér's V. Because discipline is a single dichotomous variable and all expected cell counts exceeded 5, sparse-category constraints did not arise. However, because residence and discipline were almost perfectly independent, discipline could not appreciably confound the residence–HRQoL association, and formal adjustment was therefore judged unnecessary rather than infeasible. A supplementary analysis modelling the four validated WHOQOL-BREF domain scores as separate dependent variables under the same adjusted specification was considered but could not be undertaken, as only the aggregated Global HRQoL composite was retained as the analytic outcome variable and item-level responses were not preserved, precluding recomputation of the domain scores for multivariable modelling. The multivariable findings are therefore framed throughout as pertaining to the investigator-derived composite outcome, and the corroborating domain-level evidence available in this dataset.

3. Results

Rural (n=100) and urban (n=100) athlete groups showed no significant differences in age (22.34 vs 22.60 years; $t(196.2) = -0.65$, $p=.515$), sex distribution (59% vs 54% male; $\chi^2 = 0.33$, $p=.568$, Yates-corrected), training experience (5.25 vs 5.55 years; $t(192.9) = -0.81$, $p=.418$), or training frequency (4.81 vs 5.03 days/week; $t(194.4) = -1.19$, $p=.234$) (Table 1). No statistically significant between-group differences were observed on these variables, suggesting the two samples were broadly comparable demographically and athletically; however, the absence of statistical significance does not itself demonstrate equivalence or eliminate the possibility of residual confounding by age, sex, training experience or training frequency, particularly given the moderate sample size. Groups did differ significantly in IPAQ activity category ($\chi^2 = 20.21$, $p<.001$), with rural athletes disproportionately classified as "High" activity (73% vs 43%), this itself is a study finding, not a threat to comparability, since physical activity is a primary outcome variable. Sport discipline was distributed almost identically across residence strata (Table 1). Team-sport athletes constituted 63.0% of the rural and 67.0% of the urban sample, with individual-sport athletes accounting for the remainder (37.0% and 33.0% respectively); this difference was non-significant and negligible in magnitude ($\chi^2(1) = 0.20$, $p = .656$; Cramér's $V = .04$), with observed counts departing from expectation by only two participants per cell. Because confounding requires an association between the covariate and the exposure, the near-complete independence of discipline and residence indicates that discipline is unlikely to account for any material portion of the observed rural–urban differences in sleep quality, screen time, physical activity or HRQoL.

Descriptive Statistics for the Pooled Sample (N=200) indicated acceptable distributional properties for parametric analysis (Table 2) since all skewness values were low (range −0.21 to 0.42) and the Shapiro–Wilk/Q–Q plot decision indicated that t-tests, correlations and regression analysis could be used. The overall sample of participants demonstrated a mean PSQI score of 5.46 (SD=1.98), which was slightly higher than the clinical cutoff of >5 for poor sleep. The mean screen time was 3.86 hrs/day (SD=1.35) and the mean physical activity was 3,306 MET-min/week (SD=1,225), indicating a very active sample when compared with IPAQ. WHOQOL domain scores (0–100 scale) were 63.88 (Environment) to 72.75 (Physical Health), and the Global HRQoL composite score was 67.85 (SD=6.78), indicating moderately good overall HRQoL with lower scores on the environmental and social domains.

Rural athletes showed statistically and practically significant advantages across every measured variable (Table 3). Sleep quality was better in rural athletes (PSQI M =4.80 vs 6.11; mean diff =−1.31, 95% CI [−1.82, −0.80]; $t(189.7) = -5.08$, $p<.001$, $d=0.72$, medium-to-large effect). Screen time was lower in rural athletes (3.16 vs 4.56 hrs/day; mean diff=−1.40, 95% CI [−1.72, −1.08]; $t(185.0) = -8.60$, $p<.001$, $d = 1.22$, large effect: the strongest group difference observed). Physical activity was higher among rural athletes (3,777.6 vs 2,834.8 MET-min/week; mean diff=942.8, 95% CI [625.1, 1260.6]; $t(197.4) = 5.82$, $p<.001$, $d = 0.82$, large effect).

Table 1. Demographic and Athletic Characteristics of Rural and Urban Athletes (N = 200)

Characteristic	Rural (n = 100)	Urban (n = 100)	Total (N = 200)	Test statistic (df)	*p*
Age, years, M (SD)	22.34 (2.68)	22.60 (2.95)	22.47 (2.81)	t = −0.65 (196.2)	.515
Sex, n (%)				χ^2 = 0.33 (1)	.568
Male	59 (59.0)	54 (54.0)	113 (56.5)		
Female	41 (41.0)	46 (46.0)	87 (43.5)		
Training experience, years, M (SD)	5.25 (2.40)	5.55 (2.83)	5.40 (2.62)	t = −0.81 (192.9)	.418
Training frequency, days/week, M (SD)	4.81 (1.21)	5.03 (1.39)	4.92 (1.30)	t = −1.19 (194.4)	.234
IPAQ activity category, n (%)				χ^2 = 20.21 (2)	< .001
Low	0 (0.0)	4 (4.0)	4 (2.0)		
Moderate	27 (27.0)	53 (53.0)	80 (40.0)		
High	73 (73.0)	43 (43.0)	116 (58.0)		
Sport discipline, n (%)				χ^2 = 0.20 (1)	.656
Team sports	63 (63.0)	67 (67.0)	130 (65.0)		
Individual sports	37 (37.0)	33 (33.0)	70 (35.0)		

Table 2. Descriptive Statistics for PSQI, Screen Time, Physical Activity, and WHOQOL-BREF (N = 200)

Variable	M	SD	Min	Max	Skewness
PSQI Global Score	5.46	1.98	1	12	0.31
Screen Time (hrs/day, Digital Wellbeing)	3.86	1.35	0.6	8.9	0.42
Physical Activity (MET-min/week)	3306	1225	412	8340	0.35
WHOQOL Physical Health	72.75	9.87	45.1	96.3	−0.21
WHOQOL Psychological	69.21	9.99	42.8	93.5	−0.14
WHOQOL Social Relationships	65.59	10.75	36.2	92.0	0.05
WHOQOL Environment	63.88	9.53	38.7	89.4	0.02
WHOQOL Global HRQoL (composite)	67.85	6.78	46.8	85.0	−0.10

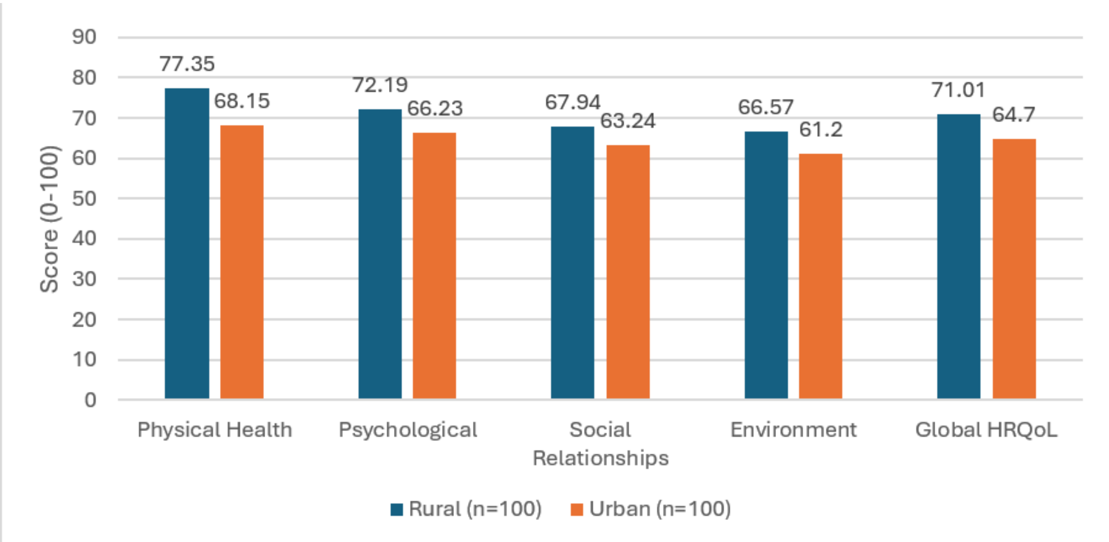

Figure 1. Rural athletes scored higher than urban athletes across all WHOQOL-BREF domains and the Global HRQoL composite.

Table 3. Rural–Urban Comparison on Sleep Quality, Screen Time, Physical Activity, and HRQoL

Variable	**Rural M (SD)**	**Urban M (SD)**	**Mean diff. (95% CI)**	**t**	**df**	**p**	**Cohen's d**
PSQI Global Score	4.80 (1.62)	6.11 (2.00)	−1.31 (−1.82, −0.80)	−5.08	189.7	< .001	0.72
Screen Time (hrs/day)	3.16 (0.99)	4.56 (1.30)	−1.40 (−1.72, −1.08)	−8.60	185.0	< .001	1.22
Physical Activity (MET-min/wk)	3777.6 (1178.2)	2834.8 (1113.4)	942.8 (625.1, 1260.6)	5.82	197.4	< .001	0.82
WHOQOL Physical Health	77.35 (8.30)	68.15 (9.92)	9.20 (6.67, 11.74)	7.12	192.0	< .001	1.01
WHOQOL Psychological	72.19 (8.80)	66.23 (10.34)	5.96 (3.30, 8.62)	4.39	193.0	< .001	0.62
WHOQOL Social Relationships	67.94 (10.26)	63.24 (10.98)	4.70 (1.75, 7.64)	3.13	197.1	.002	0.44
WHOQOL Environment	66.57 (9.67)	61.20 (8.82)	5.37 (2.81, 7.93)	4.10	196.4	< .001	0.58
Global HRQoL	71.01 (5.49)	64.70 (6.50)	6.31 (4.64, 7.98)	7.41	192.6	< .001	1.05

Table 4. Pearson Correlation Matrix among PSQI, Screen Time, Physical Activity, and HRQoL Domains (N = 200)

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. PSQI Global	—							
2. Screen Time	.19**	—						
3. MET-min/week	−.10	−.21**	—					
4. WHOQOL Physical	−.48**	−.44**	.40**	—				
5. WHOQOL Psychological	−.44**	−.42**	.27**	.61**	—			
6. WHOQOL Social	−.24**	−.33**	.22**	.38**	.34**	—		
7. WHOQOL Environment	−.30**	−.28**	.27**	.43**	.41**	.30**	—	
8. Global HRQoL	−.54**	−.53**	.42**	.82**	.77**	.64**	.68**	—

Note: *p < .05, **p < .01 (two-tailed). MET-min/week = metabolic equivalent minutes per week.

All four WHOQOL domains favored rural athletes, with effect sizes ranging from medium (Social Relationships, d=0.44) to large (Physical Health, d=1.01; Global HRQoL, d =1.05), as depicted in Figure 1. Per the table note, negative t/mean-difference values indicate higher urban scores while positive values indicate higher rural scores; Welch's correction was applied throughout given unequal variances, and the Satterthwaite-adjusted df. The correlation matrix revealed a coherent pattern of associations consistent with the study's conceptual model. All four WHOQOL domains and the Global HRQoL composite correlated negatively with PSQI (r=−.24 to −.54) and screen time (r=−.28 to −.53), and positively with MET-min/week (r=.22 to .42) — all p<.01. The Global HRQoL composite correlated most strongly with the Physical Health (r = .82) and Psychological (r = .77) domains and least strongly with Social Relationships (r = .64). Because the composite is an unweighted arithmetic mean, all four domains contribute equally to its computation by construction; this gradient therefore reflects differences in the extent to which each domain covaries with the remaining domains (Table 4) rather than any differential weighting, with Physical Health and Psychological showing the highest inter-domain correlation (r = .61) and Social Relationships the lowest average association with the other domains.

Table 5. Multiple Linear Regression Predicting Global HRQoL (N = 200)

Predictor	B	SE	β	t	p	95% CI
Constant	78.41	3.13	—	25.09	< .001	[72.25, 84.58]
PSQI Global Score	−1.55	0.18	−0.42	−8.61	< .001	[−1.90, −1.20]
Screen Time (hrs/day)	−1.91	0.28	−0.35	−6.82	< .001	[−2.46, −1.36]
Physical Activity (per 1,000 MET-min/wk)	1.57	0.28	0.26	5.61	< .001	[1.01, 2.12]
Residence (Urban = 1)	−0.18	0.83	−0.01	−0.22	.825	[−1.83, 1.46]
Age (years)	0.03	0.12	0.01	0.25	.765	[−0.19, 0.26]
Sex (Male = 1)	−1.06	0.65	−0.07	−1.63	.104	[−2.35, 0.22]

Dependent variable = WHOQOL-BREF Global HRQoL composite, Unstandardized (B) and standardized (β) coefficients shown with standard errors (SE).

Table 6. Model Summary and Overall F-Test for the Multiple Regression Model Predicting Global HRQoL

Model	R	R^2	Adjusted R^2	SE of estimate	F (df1, df2)	p
Full model (PSQI, screen time, MET-min/week, residence, age, sex)	.753	.567	.554	4.53	42.20 (6, 193)	< .001

Notably, PSQI and screen time were weakly positively correlated (r=.19, p=.006), suggesting greater screen exposure is modestly linked to poorer sleep; a small but statistically detectable relationship. MET-min/week correlated weakly negatively with screen time (r =−.21, *p* =.003), indicating a modest activity-versus-screen displacement effect. Per the table note, single asterisks denote *p*<.05 and double asterisks p<.01 (two-tailed); the pattern of exclusively negative sleep/screen correlations and positive activity correlations with HRQoL provides convergent bivariate support ahead of the multivariable model in Table 5.

The multiple regression model identified three independent, significant behavioral predictors of the Global HRQoL composite after adjusting for residence, age, and sex. PSQI was the strongest standardized predictor (B=−1.55, SE=0.18, β=−0.42, t(193) =−8.61, p<.001, 95% CI [−1.90, −1.20]): each 1-point increase in PSQI (poorer sleep) was associated with a 1.55-point decrease in Global HRQoL. Screen time was similarly robust (B=−1.91, SE=0.28, β=−0.35, t=−6.82, p<.001, 95% CI [−2.46, −1.36]): each additional hour of daily screen time was associated with a 1.91-point HRQoL decrease. Physical activity showed a positive independent effect (B=1.57 per 1,000 MET-min/week, SE=0.28, β=0.26, t=5.61, p<.001, 95% CI [1.01, 2.12]). Critically, residence lost significance once behavioral variables were added (B=−0.18, p=.825), and neither age (B=0.03, p=.765) nor sex (B=−1.06, p=.104) were significant. In this cross-sectional sample, the raw rural–urban difference in HRQoL observed in Table 3 was attenuated to non-significance once sleep quality, screen time and physical activity were entered into the model; this pattern is consistent with, but does not by itself establish, the possibility that these behavioral differences account for part of the rural–urban HRQoL gap. Because the data are cross-sectional and no formal mediation model with bootstrapped indirect effects was estimated, this attenuation should be described as an adjusted association rather than statistical mediation.

The overall regression model was statistically significant (Table 6) and explained a substantial proportion of variance in Global HRQoL: R=.753, R^2=.567, adjusted R^2=.554, F(6,193) =42.20, p<.001. An adjusted R^2 of .554 indicates the six-predictor model (PSQI, screen time, MET-min/week, residence, age, sex) accounted for over half the variance in HRQoL scores even after penalizing for the number of predictors a large effect by conventional behavioral-science benchmarks (Cohen, 1988) and unusually strong explanatory power for a self-report psychosocial outcome. The residual standard error of estimate (4.53) relative to the Global HRQoL SD of 6.78 (Table 2) further indicates good model fit. Residence, age and sex were each non-significant in the adjusted model (Table 5), whereas the three behavioral predictors were each significant at $p < .001$. This pattern is consistent with the behavioral variables accounting for the larger share of explained variance, but the relative contribution of the two predictor blocks was not formally quantified: no hierarchical or incremental R^2 analysis was conducted, and because residence is itself associated with all three behaviors (Table 3), their explained variance is partly shared and cannot be partitioned from these coefficients alone.

Although adjusted domain-level models could not be estimated (Section 2.8), three lines of evidence indicate that the principal associations are not artefacts of the composite scoring. First, every validated WHOQOL-BREF domain shows the same directional pattern as the composite: all four correlate negatively with PSQI ($r = −.24$ to $−.48$) and with objectively measured screen time ($r = −.28$ to $−.44$), and positively with physical activity ($r = .22$ to $.40$; all $p < .01$; Table 4). Second, all four domains show significant rural advantages, ranging from Social Relationships ($d = 0.44$) to Physical Health ($d = 1.01$; all $p \leq .002$; Table 3), with no null or reversed domain, so the composite-level group effect is not attributable to any single domain. Third, because the composite is an unweighted arithmetic mean of the four domains, its unstandardized regression coefficients are by construction the arithmetic mean of the corresponding domain-level coefficients under an identical predictor set; the significant composite coefficients reported in Table 5 therefore cannot arise unless the underlying domain-level associations are predominantly of the same sign and non-trivial magnitude. These considerations support, but do not substitute for, formally adjusted domain-level models, and the contribution of each behavioral exposure to specific validated domains after covariate adjustment remains untested in this study.

4. Discussion

4.1 Principal Findings

This cross-sectional comparative study revealed that rural competitive athletes experienced significantly higher levels of sleep quality, lower objectively measured smartphone screen time, higher physical activity volume and higher HRQoL when compared to their urban counterparts, with medium to large effect sizes. Poorer sleep quality, more screen time and less physical activity were each independently associated with worse HRQoL, and together with residence, age and sex they accounted for more than half the variance in HRQoL scores in the full regression model. The attenuation of the residence effect to non-significance once these behavioral variables were added is consistent with the rural–urban HRQoL gap being statistically associated with these behavioral differences rather than with residence per se; because the design is cross-sectional and no formal mediation analysis was performed, this should be interpreted as an adjusted association and not as evidence of a causal or mediating pathway. These multivariable associations pertain to the investigator-derived composite outcome; adjusted models using the four validated WHOQOL-BREF domains as separate dependent variables were not estimated, so the extent to which each behavioral exposure is independently associated with specific validated domains remains undetermined.

4.2 Sleep Quality

The mean PSQI global score was greater than the clinical cut-off of 5 (indicating poor sleep quality) in urban athletes ($M = 6.11$) but not in rural athletes ($M = 4.80$). This is somewhat similar to the findings of Gupta *et al.* (2017) who found that elite athletes scored higher on the PSQI (sleep impairment) than the average non-athletic norm, citing factors such as an early training schedule, travel and competition anxiety as reasons for this, which may be more pronounced in an urban training environment, where travel times are longer and training schedules are more intense. The current disparity of sleep between rural and urban populations is consistent with the results from general population studies showing superior sleep indices in rural areas, which may be due to a more peaceful environment, minimal light pollution, and more consistent work/agricultural routine (Walsh *et al.* 2021). The possible cause of the urban disadvantage is the cumulative impact of higher screen exposure, which in this study, is only modestly associated with PSQI ($r = .19$), via various pathways such as melatonin suppression by blue-light from the screens and pre-sleep cognitive arousal (Exelmans & Van den Bulck, 2016).

4.3 Smartphone Screen Time

Objectively measured screen time differed substantially between residence groups, with urban athletes averaging 4.56 h/day compared with 3.16 h/day among rural athletes (mean difference = 1.40 h/day, 95% CI [1.08, 1.72]; $d = 1.22$), the largest single between-group effect observed in this study. This result aligns with broader population-level data that urban populations, especially younger adults, are more digitally engaged and that they tend to have more advanced digital infrastructure, more needs to work/learn remotely, and more pervasive exposure to social media (Twenge & Campbell, 2018). Most importantly, this study was based on objective measurements of Digital Wellbeing, not self-reported measures, thereby reducing the recall bias and desirability bias found in previous studies using self-reported measures (Ellis *et al*., 2019; Parry *et al.,* 2021), thereby lending increased credibility to the size of the association between screen time and HRQoL ($r = -.53$). This is consistent with, and extends and reinforces, previous self-reported studies that have found a relationship between excessive screen time and poorer psychological and social outcomes (Twenge & Campbell, 2018), and represents an important contribution as self-reported screen-time data in athletes is limited.

4.4 Physical Activity

Both groups were predominantly active by IPAQ standards, but the modal IPAQ activity category differed significantly by residence: 73% of rural athletes were classified as 'High' activity versus 43% of urban athletes ($\chi^2 = 20.21$, $p < .001$; Table 1). This categorical difference was mirrored in the continuous MET-min/week values, which were significantly higher for rural athletes (M = 3,778) than urban athletes (M = 2,835). This is partially in line with general-population studies indicating that the rural population accumulated more incidental physical activity, (occupational, transport-related) (Loprinzi & Cardinal, 2011), as well as diverging from the assumption that urban athletes were able to access better opportunities for structured gym sessions and coaching would lead to increased activity volumes. One possible explanation is that the IPAQ-SF measures all activity, beyond structured training, and rural athletes may have more incidental activity (walking/cycling to training venues, agricultural or manual work), which may balance the advantage of more access to structured facilities for urban athletes. The positive relationship between MET-min/week and HRQoL ($r = .42$) is consistent with a large literature of physical activities association with improved quality of life in sporting and non-sporting populations (Bize *et al.,* 2007; Pucci *et al.,* 2012)

4.5 Health-Related Quality of Life

Rural athletes had significantly higher scores in all domains of the WHOQOL-BREF, with the highest difference seen in Physical Health ($d = 1.01$) and the lowest difference seen in the Social Relationships domain ($d = 0.44$). The comparatively larger Physical Health and Psychological Health gaps are consistent with the conceptual framework guiding this study, in which better sleep and lower screen time are hypothesized to relate to improved physical recovery and mood, though this pathway cannot be formally tested with the present cross-sectional data; Social Relationships was potentially buffered by team training group cohesion regardless of residence as shown by a smaller, but still significant gap.

4.6 Rural–Urban Differences

The rural-urban differences seen here must be understood socio-economically, environmentally, and technologically-infrastructurally, and not as a direct consequence of urban or rural residence, which is clearly demonstrated by the finding in the regression that residence lost predictive power with the inclusion of sleep, screen time, and physical activity. Mechanisms that could explain this include increased ambient digital connectivity and infrastructure in urban areas (which could increase screen engagement; Twenge & Campbell, 2018), potentially higher urban environmental stressors (noise, crowding, commute burden) that impact sleep (Walsh *et al.,* 2021), and rural athletes having more incidental PA, which may offset less access to specialized sports facilities (Loprinzi & Cardinal, 2011). Such explanations are consistent with, but cannot be substantiated by, the present cross-sectional data and are offered as possible, not causal, explanations. A similarly patterned rural HRQoL advantage, alongside heterogeneous findings depending on context and outcome measure, has recently been reported in general youth populations (Pano-Rodriguez *et al.,* 2025), suggesting the present athlete-specific findings fit within a broader and still-developing literature on residential context and quality of life.

The current pattern of findings is confirmed by and builds on multiple lines of evidence. The sizes of the athlete HRQoL advantage found here ($d = 1.05$ for the global HRQoL) are toward the high end of those reported in the meta-analytic literature when comparing athletes with contrasting injury or lifestyle profiles (Houston *et al.,* 2016), further supporting the idea that the HRQoL of competitive athletes is not immutable but closely follows modifiable exposures. In the same way, the finding that the benefits of being an athlete for HRQoL can be dampened or eliminated when athletic conditions are unfavorable is consistent with evidence showing that HRQoL in athletic populations is not just a function of athletic status, but also systematic with modifiable and injury-related exposures (Filbay *et al.,* 2019; Simon & Docherty, 2014).

The sleep data are very similar to data from collegiate athletes in general. In college student-athletes, Brauer *et al.* (2019) reported that sleep quality was significantly lower than optimal, and that the negative consequences of sleep were related to mood and learning performance, like in the current study, even among physically active, competitively involved youth. Here, we found a weak but significant positive correlation between screen time and PSQI ($r = .19$), which is consistent with a possible screen-related sleep-disruption pathway, and not merely a spurious relationship with this sample of young adults, given that clinical evidence confirmed that increased severity of smartphone use is associated with worse sleep quality, depression and anxiety in young adults (Demirci *et al.,* 2015).

This relationship between screen time and HRQoL ($r = -.53$) has been supported by a larger body of evidence that has found problematic and excessive smartphone use to be associated with poorer psychological functioning. Elhai, Dvorak, Levine and Hall (2017) noted that the studies examined by them also revealed that problematic smartphone use was consistently related to higher levels of anxiety and depression symptoms within them, and there was a separate correlation between the levels of perceived stress and lower life satisfaction among the university students in Samaha and Hawi (2016) study. The strong associations found in the present study with objectively logged screen time, as opposed to self-reported screen time, bolsters confidence in the relationship being true to smartphone usage and not simply shared self-report bias between the two measures, a concern that has been raised in particular given the weak or non-significant correlations between the two measures (Lee *et al.*, 2021; Hodes & Thomas, 2021).

This athlete sample found a positive association between PA and HRQoL ($r = .42$), which corroborates, and extends to athletes, a review of the literature that showed positive relationships between PA and HRQoL across several populations and measures (Marquez *et al.,* 2020). The present study extends this literature by showing that the association also exists in a sample selected specifically to have high levels of baseline activity engagement, thus indicating that the association does not appear to have an early ceiling for physical activity's effect on HRQoL.

Lastly, the observed rural/urban behaviour and HRQoL gradient is similar to the overall environmental and epidemiological evidence on urbanicity and health. Meta-analytic evidence suggests that urban residents are at increased risk of depression, anxiety, and psychotic disorders, potentially driven by high exposure to noise, crowding, and limited access to restorative environments in cities, and which may underlie the urban athletes in the present study who reported both poorer sleep and lower HRQoL. This counterintuitive result that rural athletes had higher total MET-min/week despite what was likely poor access to structured sports facilities is similar to national data showing that when controlled for structured or high intensity activity, rural residents were found to accumulate more incidental, non-leisure physical activity than urban residents (Fan *et al.,* 2014), suggesting that much of the total activity captured by IPAQ-SF in rural athletes is incidental, rather than structured, activity.

5. Strengths and Limitations

The main strengths of this study are the use of objectively assessed screen time (Android Digital Wellbeing), which addresses a well-documented limitation of self-reported screen time in the literature; the use of instruments (PSQI, IPAQ-SF, WHOQOL-BREF) with established psychometric properties in prior validation work; low multicollinearity among regression predictors, with all VIF < 2.0; a multivariable regression approach that adjusted for demographic and residential covariates; and the statistical robustness of the findings, as evidenced by internally consistent effect sizes, confidence intervals, and correlation patterns across tables, strengthened by an a priori power calculation and adherence to STROBE reporting guidelines. It should be noted that VIF is a diagnostic for multicollinearity among predictors and is conceptually distinct from internal consistency (scale reliability); item-level responses were not retained in this dataset, so sample-specific Cronbach's alpha/omega values could not be computed post hoc, and internal consistency for the PSQI, IPAQ-SF and WHOQOL-BREF instead relies on estimates reported in their original validation studies, which is itself acknowledged as a limitation. Several further caveats are relevant: the cross-sectional design precludes causal inference about the direction of the sleep–screen time–activity–HRQoL relationships (e.g., poor HRQoL may lead to decreased activity or poorer sleep, and vice versa), and the attenuation of the residence effect after adjustment reflects an adjusted statistical association rather than a formally tested mediation pathway; the relative explanatory contributions of the behavioral and demographic predictor blocks were not formally partitioned, as no hierarchical regression or incremental R^2 analysis was performed, so statements about the relative importance of the behavioral variables rest on their individual coefficients rather than on quantified variance decomposition; the purposive/quota sampling design and the study-specific operational definition of rural/urban residence limit generalizability beyond the specific regions, residence criteria, and sports contexts sampled; the distribution of sport discipline is now reported by residence stratum and was closely balanced (Table 1), making confounding by discipline improbable, but competition level, although recorded, is not reported or adjusted for, so residual confounding by competitive standard which may plausibly track training load, travel burden and sleep opportunity cannot be excluded, the binary team/individual classification obscures heterogeneity between disciplines within each category, and unmeasured athletic exposures such as seasonal training phase and coaching context were not captured; the Global HRQoL composite used as the primary outcome is an investigator-derived unweighted average of the four WHOQOL-BREF domain scores rather than a standard, independently validated WHOQOL-BREF output, its equal weighting of the four domains is an assumption rather than an empirically derived measurement structure, and a formal sensitivity analysis using the four validated domain scores as separate adjusted outcomes could not be conducted in this dataset (Section 2.8), so although all four domains show concordant bivariate and group-difference patterns (Section 3.7), the principal multivariable findings should be read as applying specifically to this composite and compared with studies employing standard HRQoL indices only with corresponding caution; although screen time was objectively measured, self-report measures (PSQI, IPAQ-SF, WHOQOL-BREF) were also included, which introduces social-desirability and recall bias; the moderate criterion validity of the IPAQ-SF against accelerometry ($\rho \approx .30$, as noted in the instrument's known psychometric limitations) may lead to non-trivial measurement error for the physical activity variable, a key predictor in the regression model, that could attenuate or bias its estimated relationship with HRQoL; and, because screen time was measured exclusively via Android smartphones, users of iOS devices were not included, resulting in a platform-based selection bias.

6. Conclusion

In this cross-sectional comparison of competitive athletes aged 18–30 years, rural athletes reported better sleep quality, lower objectively measured screen time, higher physical activity, and higher HRQoL than urban athletes, with effect sizes ranging from medium to large across all measures. Sleep quality, screen time, and physical activity were each independently associated with HRQoL, and together with residence, age, and sex, these variables accounted for 56.7% of the variance in the investigator-derived Global HRQoL composite, an outcome that is not a standard validated WHOQOL-BREF index (adjusted R^2 = .554); this reflects the combined six-predictor model, not the contribution of any single behavior. The raw rural–urban difference in HRQoL was attenuated to non-significance once sleep, screen time, and physical activity were added to the model, an adjusted association consistent with, but not proof of, behavioral pathways underlying the residence gap; the cross-sectional design does not permit causal or mediational conclusions, and reverse or bidirectional relationships (e.g., poorer HRQoL reducing activity or worsening sleep) cannot be excluded. These findings nonetheless have practical relevance: they suggest that sleep hygiene, screen-time management, and physical activity promotion are plausible behavioral targets for residence-sensitive lifestyle interventions in athlete health management, particularly for urban athletes who showed a less favorable behavioral and HRQoL profile. Future research should use longitudinal or intervention designs to test whether modifying these behaviors changes HRQoL over time, incorporate sport type, competition level, and socioeconomic covariates more fully into rural–urban comparisons, and, as a priority, re-estimate the present adjusted models using the four validated WHOQOL-BREF domain scores as separate outcomes, together with established global HRQoL instruments, to confirm that the behavioral associations reported here are independent of the composite scoring adopted in this study.

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Author Contribution Statement

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