JKMS

Original Article
Psychiatry & Psychology

Check for updates

OPEN ACCESS

The Association Between Temperament and Characteristics, Smartphone App Use Patterns and Academic Performance of University Students

Jea Woog Lee [ID],[1] Sung Je Park [ID],[1] Soyeon Kim [ID],[2] Un Sun Chung [ID],[3] and Doug Hyun Han [ID] [2]

[1]College of Sport Science, Chung-Ang University, Anseong, Korea
[2]Department of Psychiatry, Chung-Ang University School of Medicine, Seoul, Korea
[3]Department of Psychiatry, Kyungpook National University, School of Medicine, Daegu, Korea

ORCID iDs
Jea Woog Lee [ID]
https://orcid.org/0000-0001-8112-407X
Sung Je Park [ID]
https://orcid.org/0000-0002-8459-0188
Soyeon Kim [ID]
https://orcid.org/0000-0002-2753-0875
Un Sun Chung [ID]
https://orcid.org/0000-0003-3871-1425
Doug Hyun Han [ID]
https://orcid.org/0000-0002-8314-0767

ABSTRACT

Background: Smartphone use patterns may predict daily life efficacy and performance improvements in sports. Additionally, personal characteristics may be associated with smartphone overuse.

Methods: We investigated the correlation between the temperament and character inventory (TCI) and academic performance using smartphone log data. We hypothesized that the elite and general groups, divided based on academic performance, differed according to the TCI and downloadable smartphone apps (applications). Additionally, we hypothesized a correlation between smartphone app usage patterns and TCI. A total of 151 students provided smartphone log data of the previous four weeks. They also completed the TCI and provided academic records of the previous year.

Results: The first and second most frequently used apps by both groups of students were social networking and entertainment, respectively. Elite students scored higher on novelty seeking, reward dependence, persistence, self-directedness, and self-transcendence than general students. In all participants, the usage time of serious apps was correlated with the scores for novelty seeking (r = 0.32, $P < 0.007$), reward dependence (r = 0.32, $P < 0.007$), and self-transcendence (r = 0.35, $P < 0.006$). In the elite group, the usage time of serious apps was correlated with the scores for novelty seeking (r = 0.45, $P < 0.001$), reward dependence (r = 0.39, $P = 0.022$), and self-transcendence (r = 0.35, $P = 0.031$). In the general group, the usage time of serious apps was correlated only with self-transcendence (r = 0.32, $P < 0.007$).

Conclusion: High usage time of serious apps can help sports majors to excel academically. Particularly among sports majors, serious apps are related to activity, the desire for rewards and recognition, and the tendency to transcend themselves.

Keywords: Smartphone Log Data; Data Science; Temperament and Character Inventory; Novelty Seeking; Reward Dependence; Serious App

INTRODUCTION

Smartphones have become an indispensable part of daily life. According to a 2020 report by the Pew Internet and American Life Project, 96% of college students and 89% of non-students of the same age had a cellphone.[1] Smartphones provide access to vast amounts of information, and increase convenience in daily life through a wide range of applications[2] including news, social media, entertainment, and education. Daily benefits include cameras, navigation, and schedule notifications. Today's college students are the first fully grown digital natives. Incorporating digital technologies into daily life among this cohort is a cultural norm.[3]

Despite the numerous benefits of smartphone use, they can also be harmful.[4] Excessive screen use is associated with poor sleep and academic performance in adolescents and young adults.[5] Similarly, low self-control results in excessive smartphone usage and poor academic achievement.[6] Life attitudes associated with smartphone use result from temperament and personality traits.[7] As smartphones become more accessible, a study on the relationship between smartphone usage habits, personality, temperamental characteristics, and grades of college students in their 20s is needed.

Smartphone usage patterns have a relatively greater influence on school achievement than usage time.[8] In addition, the use of smartphones for productive purposes is related to excellent academic performance.[9] Therefore, there is a strong causal relationship between smartphone use time and school achievement.[10] Researchers have studied the relationship between smartphone usage and grades in college students, and reported that participants were divided into high- and low-grade groups according to the type of app used.[4] In addition, studies have suggested a relationship between smartphone usage and academic performance in adolescents, young adults, and college students.[11,12]

In previous studies of sports players and students, smartphone app use pattern predicted sports and academic performances.[13] Comparing the smartphone usage patterns of excellent and general players, that the former used useful apps more often.[14,15] In addition, smartphone use is closely related to personal achievement for most students and athletes, regardless of their major.[16]

Smartphone usage information can be acquired in various ways. Self-report questionnaire survey on smartphone usage time and app usage.[17,18] Lin et al.[19] and Zimmermann installed a smartphone usage tracking app to collect data.[20] However, these methods have several limitations. First, subjective responses regarding smartphone usage may differ according to individual cognitive abilities and interests.[21] Second, there is the possibility of response bias, with respondents underreporting their smartphone usage time and frequency, or being dishonest about the apps they used.[22] Third, the procedure of installing a separate app for tracking smartphone usage is a limitation of data collection.[23]

Smartphones have built-in screen time features. Wang et al.[24] used iOS Screen Time and Android's Digital Wellbeing data to compare users' smartphone security attitudes across countries. Ohme et al.[22] demonstrated the need for research on smartphone log data by comparing the Screen Time and user self-reports. Rosenthal et al.[25] reported high accuracy in comparing self-reported data on depression and smartphone usage time and Screen Time or Digital Wellbeing. Determining the correlation between the smartphone usage habits of

infants and toddlers, and the degree of interaction at home, Lauricella et al.[26] reported that smartphone usage data should be viewed as a warning message.

Most studies on the relationship between personality, temperament, and smartphone usage habits used self-reported data.[27-31] Personality and temperament studies have also been conducted using commercial smartphone usage measurement apps.[19,20] However, few studies have examined the relationship between smartphone log data and personality and temperament. Lee et al.[13] classified app usage history from mobile log data for four weeks into four types ("social networking sites [SNS]," "entertainment," "games," and "serious"), and reported a correlation between golf players' performance and smartphone usage patterns. This study collected smartphone usage patterns and app usage history using Screen Time and Digital Wellbeing features on iOS and Android, respectively. We examined the correlation between the academic performance of physical education students and their smartphone app use patterns in an environment where physical activity classes and theoretical classes were combined.

Several studies have investigated the relationship between smartphone use and personality. The Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) could be predicted from smartphone usage data.[32,33] In addition, the Big Five personality traits influence the use of specific apps.[24,34,35]

Personal traits such as extraversion and sociability are associated with the overuse of social media.[36] Schoedel et al.[37] conducted a study on the temperament associated with behavioral addiction; specifically, they investigated the relationship between Internet addiction and temperament. Additionally, studies have revealed the difference between the temperamental characteristics visible in behavioral addictions, and those associated with smartphone addiction through the relationship between smartphone use and individual temperament.[38] Zeidan et al.[39] reported that the more depressive one's temperament, the greater the smartphone addiction.

Previous studies have mainly explored the association between the causes of behavioral addiction (tobacco, alcohol, and drugs) and temperament and character inventory (TCI).[40-42] In addition, they explored the relationship between nomophobia, temperament, and personality, suggesting a correlation between the fear of not being able to access a mobile phone and personality.[43] The few studies that investigated the relationship between the TCI and smartphone use focused on problematic smartphone behavior, not the individual characteristics that appear in general smartphone use.[7,44] Thus, it is important to explore whether the TCI can aid in the formulation of a research approach for non-addicted smartphone users.

Studies have focused on the relationship between personality and academic performance. As a predictor of academic performance, the conscientiousness of the Big Five had a positive correlation with academic performance,[45] whereas neurotic factors and affinity factors had a negative correlation.[46] In addition, there is also interest in the performance ability of personality to conceptually link personality with academic performance. Attempts have been made to integrate personality and academic performance, but consistent and repeatable correlations are difficult to obtain. When trying to understand human performance, it is very meaningful to examine how the two variables work together.[47] Considering that these factors are related to each other, personality and academic performance factors are involved in human performance, especially in students' academic performance.[48] Temperament is a factor that determines academic performance, mainly in children.[7,18] In addition, types of

temperament of university students can be classified as favorable ones for their well-being, academic performance, and school life adaptation.[49]

Among research studies that have proven the relationship of academic performance with characteristics and temperament, it is difficult to find a study that combines sports and academics in the field of physical education. Some studies have shown that physical activity through exercise participation has a positive effect on academic performance, with personality and temperament being important intervention variables.[50-52] However, it is a different matter to understand characteristics of students majoring in physical education who aim to obtain better grades for both sports and academics. It is necessary to find out the characteristics and temperament for achieving positive academic performance of students majoring in physical education with both characteristics of an athlete and an academic student.

Therefore, this study assumes a correlation between academic performance and personality factors and that a certain combination affects the academic achievement and stagnation of college students. In addition, when examining the correlation between academic performance and personality, personality is divided into genotype (temperament) and phenotype (characteristic).[53]

Thus far, the correlation between academic performance and the TCI for the smartphone usage patterns of college students majoring in physical education has not been thoroughly investigated. Even though a few studies have examined the relationship between smartphone habits, personality, and temperament,[11,54,55] not as many have shown correlations between smartphone app usage patterns and personal characteristics. Therefore, the objective of this study was to investigate the correlation between TCI and academic performance through mediating effects of app use pattern.

METHODS

Participants

The participants were 151 students majoring in sports at a renowned university in Korea. The inclusion criteria were as follows: 1) aged 20–25 years, 2) usage of smartphone apps for at least the past month, and 3) activation of the log data monitoring function on the smartphone. The exclusion criteria were as follows: 1) past or current history of medical or psychiatric disorder, including attention deficit hyperactivity disorder, substance use disorder, and Internet gaming disorder, problematic behaviors related to smartphone use, and comorbidities judged to require medical access; 2) those who used two or more smartphones; and 3) those who used apps on both smartphones and iPads.

A total of 151 sports majors were assigned to two groups based on academic performance: elite (n = 37) and general (n = 114). The elite group was defined as students who got an A grade in the previous semester. The academic grades included "A," "B," "C," "D," and "E," calculated using the mean of the total subjects selected by the student and the awards won at sports competitions. If students received awards at sports competitions, they were given additional credits for better academic grades.

Grade A was established based on the group of students whose academic performances were within the top 30% of the group as a leading player, having won a prize in individual events

and individual record titles in group events. Grade B consisted of the following: 1) a group of students with top 30–50% academic performances while holding individual events as a leading player and individual record titles as a leading player; and 2) a leading player who had no individual event winning record or group event individual record title whose grade was in the top 30%. Grade C consisted of the following: 1) a leading player in individual events, with individual record titles in team events, but in the bottom 50% of academic grades; 2) a leading player within top 30–50% academic grades without personal events or individual records; and 3) a group of students whose grades were within the top 30% as non-main players. Grade D consisted of the following: 1) a main player who had no winning history in individual events or individual record titles in a group event, and scored in the bottom 50% in academic performance; and 2) not a main player with a score of 30–50% at academic performance. Grade E consisted of non-main players and the bottom 50% in academic performance.

Study design

This was a four-week observational study. The participants were asked to provide smartphone log data for the previous four weeks from the point of response, which were transmitted to the researcher as a photo file. In addition, the participants responded to a survey on age, grade, academic performance, and TCI.

Smartphone app use pattern

Based on the time and frequency of use of each app from smartphone log data, we classified 3,500 apps into 20 categories.[56] The iPhone has the following detailed app types on the official application developer webpage: books, business, education, entertainment, finance, food & drink, games, health & fitness, lifestyle, magazines & newspapers, medical, music, navigation, news, photo & video, productivity, reference, shopping, social networking, sports, stickers, travel, utilities, and weather. Android phones have the following detailed app types on the Google Play Store: books and reference, business, comic, communication and social, decoration, education, finance, game, health, lifestyle, media and video, medical, music and audio, news, personalization, photo, productivity, shopping, traffic and travel, and weather. However, as each OS application type was different, there were too many applications for analysis. Therefore, the applications were merged and the categories were rearranged. We classified the 20 initially identified categories into four application types: social networking (SNS, blogs, cafés, video calling, and messengers), entertainment (YouTube, TikTok, music apps, Netflix, podcasts, webtoons, media apps, and games), serious apps (Internet browser, schedule, e-books, creativity [camera, photo, video], education, and diaries), and others (banking, shopping, and delivery apps).[13] These four classifications of apps have already been used in our previous study on the relationship between golf performance and smartphone app use pattern.[13] Serious apps included those used by participants to support their studies.[57-59] "Others" consisted of apps not covered by previous studies or included in different categories in varied studies.[13,60]

TCI revised

The TCI is a multidimensional scale that distinguishes between innate temperament from birth and personality that shows social maturity while growing up.[61] Temperament traits are defined in terms of individual differences in associative learning in response to areas of novelty seeking, harm avoidance, reward dependence, and persistence.[61]

This questionnaire comprised 240 items (five on validity) on a five-point Likert-type response scale, grouped into four temperament dimensions (novelty seeking, harm avoidance,

reward dependence, and persistence) and three-character dimensions (self-directedness, cooperativeness, and self-transcendence). This measurement tool has been validated in general and elite Korean university students,[62,63] and construct equivalence has been verified.[64]

Novelty seeking is often associated with risk-taking and exploratory features, as well as self-regulatory skills such as limiting impulsivity. Harm avoidance is related to the inhibition of behaviors, passivity, avoidance, shyness, and rapid fatigability. Reward dependence shows the maintenance or continuation of ongoing behaviors, sentimentality, and social attachment.[65] Persistence is associated with heritable bias toward continuing and persevering without rewards.[66]

In addition, the characters are thought to reflect epigenetic influences on behaviors in response to social stimuli.[67-69] Self-directedness is associated with autonomy and life purpose, and cooperativeness is related to positive relationships with others. Finally, self-transcendence is associated with personal growth and self-actualization.[70]

Factor analysis for validity and reliability

To verify the validity and reliability of the data collected through questionnaires in the survey, confirmatory factor analysis (CFA) and reliability analysis were conducted (**Table 1**). The maximum likelihood was applied to the CFA to test the convergent validity. Resulting values of construct reliability and average variance extracted for the convergent validity appeared in ranges of 0.902–0.939 and 0.716–0.758 based on criteria of levels above 0.70 and 0.50, respectively. In the meantime, values of indices of conformance to the conceptual model of CFA appeared to exceed 0.9 (Tucker-Lewis index [TLI] = 0.933, comparative fit index [CFI] = 0.917), whereas values of root mean square error of approximation (RMSEA) and root mean square residual (RMR) appeared to fall below 0.048 and 0.051, respectively, which were regarded to be favorable. As a result, all values of the goodness of fit satisfied the criteria of acceptance.

The reliability of the collected data presented in terms of internal consistency was tested by calculating the coefficient of Cronbach's α. It was found that the Cronbach's α was 0.852 for TCI, 0.880 for serious app, and 0.872 for academic performance, thus confirming the reliability of collected data (**Supplementary Table 1**).

Table 1. Demographic and temperamental characteristics

Variables	Elite students (n = 37)	General students (n = 114)	Statistics
Age, yr	22.65 ± 1.53	22.39 ± 1.72	z = 1.04, P = 0.301
Gender (men/women)	62/52 (54.4/45.6)	21/16 (56.8/43.2)	χ^2 = 0.06, P = 0.854
School grade			χ^2 = 0.96, P = 0.812
1	6 (16.2)	19 (16.7)	
2	10 (27.0)	40 (35.1)	
3	14 (37.8)	37 (32.5)	
4	7 (18.9)	18 (15.8)	
Temperament			
Novelty seeking	33.41 ± 8.60	26.50 ± 9.94	z = 3.35, P = 0.007*
Harm avoidance	25.51 ± 6.11	23.09 ± 9.61	z = 1.23, P = 0.223
Reward dependence	21.83 ± 2.91	18.51 ± 4.71	z = 3.77, P = 0.006*
Persistence	8.57 ± 1.41	7.13 ± 2.24	z = 3.81, P = 0.006*
Characteristics			
Self-directedness	35.30 ± 5.92	30.86 ± 8.04	z = 3.04, P = 0.009*
Cooperativeness	34.84 ± 4.21	34.23 ± 7.83	z = 0.07, P = 0.953
Self-transcendence	44.05 ± 11.31	31.35 ± 18.62	z = 3.12, P = 0.008*

Values are presented as number (%) or mean ± standard deviation.
*Statistically significant.

Data analysis

Data were analyzed using IBM SPSS Statistics & AMOS (version 25.0; IBM Corp., Armonk, NY, USA). The Kolmogorov-Smirnov test was performed to determine data normality. In addition, a Mann-Whitney *U* test and the χ^2 test were performed to compare academic performance, smartphone log data, and the TCI of elite and general students. Effect size was assessed using independent *t*-tests with Cohen's d, which we interpreted as follows: 0.0 < d < 0.2, small; 0.3 < d < 0.5, medium; d > 0.6, large.[71]

Controlling for covariates—including demographic characteristics, TCI, and smartphone app use patterns—a hierarchical logistic regression analysis was adopted. In a multiple hierarchical regression analysis of elite students, a discrete set of hierarchical variables was added: Model 1: demographic characteristics; Model 2: demographic characteristics + TCI; Model 3: demographic characteristics + TCI + smartphone app use pattern. The dependent variable of the "elite student" and the "general student" were coded as "1" and "0," respectively.

Pearson's correlation analysis were conducted to evaluate the correlation between the serious app usage time and temperament and characteristics scores, including novelty seeking, reward dependence, and self-transcendence in the elite group. All tests were performed with two-sided significance levels of α < 0.05.

TCI and serious app use time were used for path analysis. CFA and reliability analysis were performed to analyze the validity and reliability of academic performance data. Path analysis was conducted to examine the relationship between students' TCI and serious app use time by dividing the academic performance of elite physical education students into theoretical performance and sports performance.

Ethics statement

The study was approved by the Chung-Ang University Institutional Review Board (reference number: 1041078-202009-HRSB-290-01), and all participants provided written informed consent. The study was conducted in accordance with the Declaration of Helsinki.[72]

RESULTS

Demographic and temperamental characteristics

The mean ± standard deviation of age, academic performance scores, and TCI score in the overall sample were 22.52 ± 1.63 years, 3.52 ± 0.78, and 26.80 ± 9.99, respectively.

There were no significant differences in age (z = 1.04, *P* = 0.301), gender ratio (χ^2 = 0.06, *P* = 0.854), or school grade (χ^2 = 0.96, *P* = 0.812) between the elite and general students (**Table 1**).

Compared to general students, elite students scored higher on novelty seeking (z = 3.35, *P* = 0.007), reward dependence (z = 3.77, *P* = 0.006), persistence (z = 3.81, *P* = 0.006), self-directedness (z = 3.04, *P* = 0.009), and self-transcendence (z = 3.12, *P* = 0.008) (**Table 1**).

Comparison of app use patterns of elite and general students

The most frequently used app category in both groups of students was social networking, followed by entertainment. However, regarding the third most frequently used app category, serious apps were more popular among elite than general students (**Table 2**).

Table 2. Comparison of app use patterns between elite and general students

Variables	Elite students (n = 37)	General students (n = 114)	Statistics
Frequently used apps			
Social networking as first choice	21 (56.8)	67 (58.8)	$\chi^2 = 0.05$, $P = 0.852$
Entertainment as second choice	22 (59.4)	65 (57.0)	$\chi^2 = 0.07$, $P = 0.793$
Serious as third choice	19 (45.9)	36 (31.6)	$\chi^2 = 4.72$, $P = 0.031$
App use time (hours:minutes)			
Total	108:28 ± 72:33	113:51 ± 102:10	z = 1.42, $P = 0.164$
Social networking	47:18 ± 33:11	49:17 ± 23:49	z = 0.68, $P = 0.504$
Entertainment	51:43 ± 35:39	56:43 ± 33:05	z = 1.23, $P = 0.223$
Serious	7:30 ± 9:02	3:51 ± 6:12	z = 2.79, $P = 0.009^*$
Others	2:15 ± 5:00	5:05 ± 15:31	z = 1.95, $P = 0.084$

Values are presented as number (%) or mean ± standard deviation.
*Statistically significant.

There was no significant difference in the total smartphone usage time between elite and general students (z = 1.42, $P = 0.164$). However, elite students used serious apps for longer than general students (z = 2.79, $P = 0.009$) (**Table 2**).

Hierarchical logistic regression analysis for the determining elite student group

Among the three models, Models 2 and 3 were significantly associated with the elite student group. With step χ^2/p (42.9/0.001 and 11.3/< 0.042), TCI and smartphone app usage patterns could predict the elite student group.

In Model 3 (demographic + TCI + smartphone app use pattern), model χ^2 (55.1/< 0.001), and Nagelkerke's R^2 (0.455) (45.5% of the variance in the dependent variable of the elite students) indicated that Model 3 was adequate for predicting the elite student group. According to the Wald statistics for all independent variables, high novelty seeking, reward dependence, self-transcendence, and more smartphone serious app use time were significant predictors of elite students (**Table 3**).

Correlations between TCI scores and app use time

In all participants, the usage time of serious apps was correlated with novelty seeking (r = 0.32, $P = 0.007$), reward dependence (r = 0.32, $P = 0.007$), and self-transcendence (r = 0.35, $P = 0.006$). In the elite group, the usage time of serious apps was correlated with novelty seeking (r = 0.45, $P = 0.001$), reward dependence (r = 0.39, $P = 0.022$), and self-transcendence (r = 0.35, $P = 0.031$). In the general group, the usage time of serious apps was correlated only with the self-transcendence score (r = 0.32, $P = 0.007$) (**Fig. 1**).
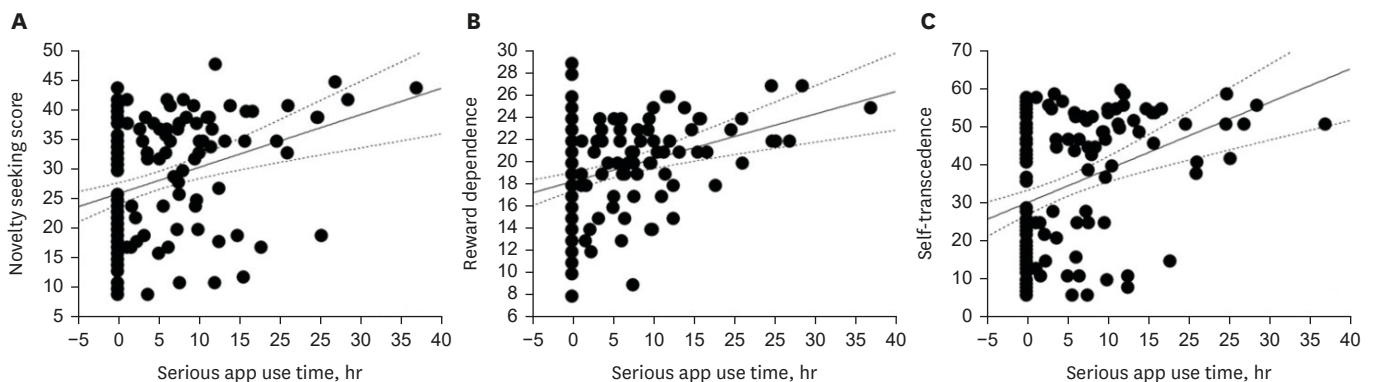
Fig. 1. The correlations between biogenetic traits and app use time. (**A**) The correlation between the use time of serious app and the scores of novelty seeking, r = 0.32, $P = 0.007$. (**B**) The correlation between the use time of serious app and the scores of reward dependence, r = 0.32, $P = 0.007$. (**C**) The correlation between the use time of serious app and the scores of Self-Transcendence, r = 0.35, $P = 0.006$.

Table 3. Hierarchical logistic regression analysis

Category		Model 1				Model 2				Model 3			
		B	Wald	OR	95% CI	B	Wald	OR	95% CI	B	Wald	OR	95% CI
Demo	Age	0.086	0.560	1.090	0.870–1.366	0.109	0.537	1.115	0.761–1.407	0.047	0.080	1.049	0.750–1.444
	Sex	0.067	0.031	1.070	0.503–2.275	−0.171	0.131	0.843	0.352–2.287	−0.450	0.723	0.638	0.261–1.964
	Edu	0.016	0.050	1.016	0.885–1.166	0.008	0.008	1.008	0.829–1.169	0.010	0.011	1.010	0.836–1.200
TCI	NS					0.074	5.430	1.077*	1.002–1.143	0.071	4.369	1.074*	1.001–1.144
	HA					0.117	7.251	0.889	0.742–0.935	0.186	1.671	1.031	0.751–0.932
	RD					0.285	8.773	1.330*	1.021–1.618	0.258	5.771	1.294*	1.038–1.579
	Ps					0.333	3.353	1.395	0.884–1.875	0.286	1.903	1.331	0.880–1.982
	SD					0.070	2.206	1.072	0.970–1.172	0.067	1.673	1.069	0.964–1.177
	Co					0.084	3.585	1.083	0.745–0.929	0.086	1.680	1.084	0.718–0.910
	ST					0.097	0.019	1.013*	1.001–1.122	0.093	0.016	1.090*	1.064–1.128
App use pattern	Total									0.002	0.091	1.000	0.999–1.000
	SNS									0.003	0.674	1.000	0.999–1.000
	Ent									0.010	1.783	1.000	0.787–0.978
	SER									0.077	3.911	1.059*	1.001–1.117
	Others									0.057	3.183	1.000	0.989–1.011
Indices	Model												
−2 LL	168.201		167.387				124.409				113.091		
Step χ²/P	N/A		0.8/0.86				42.9/0.001				11.3/< 0.04		
Model χ²/P	N/A		0.8/0.86				43.7/< 0.001				55.1/< 0.001		
NagR²	N/A		0.008				0.375				0.455		
Class accur	75.5		75.5				84.8				87.4		

−2LL, −2 log likelihood, NagR2; class accur, classification accuracy (%), dependent variable, elite student group, Model 1: Demo, Model 2: Demo + TCI, Model 3: Demo + TCI + smartphone app use pattern (app use pattern).

OR = odds ratio, CI = confidence interval, Demo = demographic characteristics, Edu = educational year, NS = novelty seeking, HA = harm avoidance, RD = reward dependence, Ps = persistence, SD = self-directedness, Co = cooperativeness, ST = self-transcendence, SNS = social network service, Ent = entertainment, SER = serious app, −2LL = −2 log likelihood, TCI = temperament and character inventory, class accur = classification accuracy.

*$P < 0.001$.

Path analysis for TCI, serious app use pattern, and academic performance

The path analysis was conducted to verify the relation of the model of factor selected for the present study. The maximum likelihood was used for the analysis to estimate relevant parameters. The estimation showed values of normed fit index = 0.945 (≥ 0.90), TLI = 0.963 (≥ 0.90), and CFI = 0.970 (≥ 0.90), while values of RMR and RMSEA were derived as 0.029 (≥ 0.08) and 0.060 (≥ 0.08), respectively. Therefore, all indices of the goodness of fit appeared to satisfy the criteria. They showed favorable conformance of the research model based on the criteria.

Results of the path analysis conducted prior to comparison of groups in the research model to verify the research model of the entire participants are shown in **Table 4** and **Fig. 2**. There were statistically significant relationships of serious app use pattern with novelty seeking (t = 6.387, $P = 0.012$), reward dependence (t = 6.210, $P = 0.012$), and self-transcendence (t = 5.990, $P = 0.013$). Theoretical performance showed statistically significant relationships with reward dependence (t = 8.214, $P = 0.010$) and persistence (t = 5.837, $P = 0.013$). Sports performance showed statistically significant relationships with novelty seeking (t = 6.967, $P = 0.011$) and persistence (t = 6.226, $P = 0.012$). In addition, serious app use pattern showed significant relations with theoretical performance (t = 11.495, $P = 0.010$) and sports performance (t = 10.348, $P = 0.010$).

DISCUSSION

Compared with general students, elite students showed higher scores for temperament, including novelty seeking, reward dependence, and persistence, as well as for characteristics

Table 4. Result of path analysis

Path			β	SE	t-value
NS	→	Serious app	0.369	0.027	6.387***
RD	→	Serious app	0.313	0.028	6.210***
P	→	Serious app	0.209	0.082	5.612*
SD	→	Serious app	0.022	0.042	0.249
ST	→	Serious app	0.291	0.070	5.990***
NS	→	Theoretical performance	−0.100	0.089	−1.769
RD	→	Theoretical performance	0.455	0.024	8.214***
P	→	Theoretical performance	0.264	0.031	5.837**
SD	→	Theoretical performance	0.089	0.091	0.318
ST	→	Theoretical performance	0.114	0.072	2.124
NS	→	Sports performance	0.382	0.027	6.967***
RD	→	Sports performance	0.102	0.087	1.815
P	→	Sports performance	0.314	0.025	6.226***
SD	→	Sports performance	0.001	0.093	0.021
ST	→	Sports performance	0.012	0.092	0.071
Serious app	→	Theoretical performance	0.578	0.021	11.495***
Serious app	→	Sports performance	0.531	0.022	10.348***

χ^2 = 144.371, df = 64, P value = 0.001, Tucker-Lewis index = 0.918, comparative fit index = 0.906, root mean square error of approximation = 0.057, root mean square residual = 0.064.
SE = standard error, NS = novelty seeking, RD = reward dependence, P = persistence, SD = self-directedness, ST = self-transcendence.
*P < 0.050, **P < 0.010, ***P < 0.001.

such as self-directedness and self-transcendence. In a previous study, novelty seeking was higher in college students with low academic performance, which contradicts the present results.[73] Cloninger et al.[61] reported that the higher the novelty seeking, the more exploratory
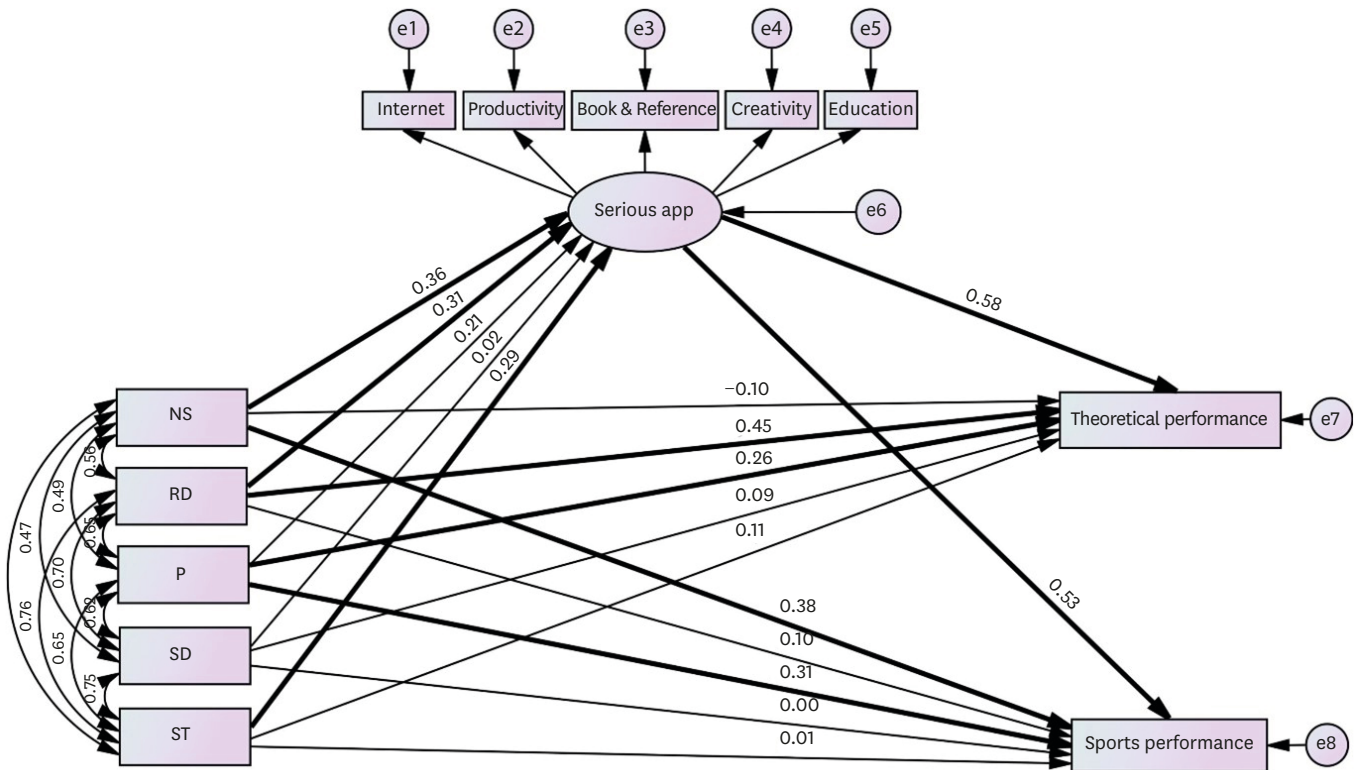
Fig. 2. Path analysis of temperament and character inventory, serious app and theoretical/sports performance.
NS = novelty seeking, RD = reward dependence, P = persistence, SD = self-directedness, ST = self-transcendence.

and impulsive but extroverted and active the individual. Student athletes should be involved in both academic and sports performance.[74,75] In both academic and sports performance, novelty seeking is known to be associated with excellent performance.[76-82] Extroversion required in sports activities is predicted to be the cause of effective academic performance in sports majors.[64,76,77,83]

Reward dependence is a tendency toward social reward behavior; further, students with high academic performance tend to seek recognition from others through high academic performance.[61,84,85] In other words, we can confirm previous findings showing the tendency of reward dependence in both elite athletes[79,86] and elite students.[87,88] People with high persistence scores are considered industrious, stubborn, steady, and stable despite frustration, whereas those with low persistence scores are considered unstable and lazy.[89] In particular, a strong tendency toward persistence can be observed in celebrities and famous athletes,[78,90] and it is an important temperamental cause of high performance in various fields.[91] Therefore, college students majoring in sports who are inquisitive but impulsive and easily bored show lower academic performance, whereas those with a more diligent and steady personality have higher academic performance.

In a previous study, students with low academic performance spent more time using SNS and entertainment apps[92,93]; however, in this study, there was no difference between elite and general students in this regard. In addition to the overall high novelty-seeking tendencies, the high activity, and social needs of physical education students[94] and the self-expression needs of athletes are related to this result.[95] This indicates that a variety of other factors may determine academic performance, and that social media use may not necessarily be detrimental to academic performance.[96] It was found that elite students with high academic performance spent more time using serious apps than general students. In addition, they actively utilized an e-learning app to improve students' concentration and learning effects.[97] A prior study showed that active study data collection using an Internet browser was associated with high academic performance in college students.[98] Many athletes spent much time using serious apps for self-management, which include image analysis, scheduling, diet, and sleep.[99-102] Smartphone usage time had no significant correlation with academic achievement; previous findings confirm that keeping smartphones out of reach led to academic success contradicts this finding.[103,104] Smartphone usage patterns had a relatively higher impact on academic performance compared with smartphone usage time.[11] In addition, the use of smartphones for productive purposes was associated with high academic performance.[105]

In Model 3 of the hierarchical logistic regression of the current study, TCI (high novelty seeking, reward dependence, and self-transcendence) and smartphone app use pattern (use of serious apps) could predict elite students. In addition, the usage time of serious apps was correlated with novelty seeking, reward dependence, and self-transcendence scores in all participants. In the elite group, the usage time of serious apps was correlated with novelty seeking, reward dependence, and self-transcendence scores.

Elite sports majors and elite athletes shared high levels of novelty seeking.[78,106] These results were in line with those of previous studies of athletes and students. Elite sports majors and medical students with high academic performance shared smartphone usage habits.[38,107] It can be predicted that they show the dispositions of both excellent players and elite students. In addition, most students with high academic performance display high

reward dependence.[85,108] High reward dependence in elite students may be associated with frequent use of serious apps to receive feedback on their abilities.[97,109-112] Personality self-transcendence is correlated with serious app usage time in both elite and general students,[113] emphasizing the importance of digital content in helping people with personality traits that seek self-transcendence. In addition, self-transcendence is related to well-being, self-management, and quality of life.[114] The positive effects of serious apps on self-management and quality of life have been demonstrated.[115] Both students and athletes report that sleep management apps lead to personal performance and physical health, as well as personal psychological improvements.[116,117] Additionally, continued use of serious apps improved behavior, lifestyle, and health.[62] Self-transcendence is related to the fulfillment of an individual's mental health needs.[118]

Similar results were also found in path analysis. High novelty seeking, reward dependence, and self-transcendence of elite physical education students were found to lead to a serious app use pattern. In the performance process, the academic performance of elite physical education students was divided into theoretical performance and sports performance and set as a dependent variable. TCI factors affecting theoretical performance were found to be reward dependence and persistence. It was confirmed that students with a high reward dependence had a tendency to desire for social recognition as a factor that could increase the academic performance of students majoring in physical education.[64,81] In addition, high persistence was found to be associated with the behavior of continuing steady and stable effort to achieve a high theoretical performance.[83,84] On the other hand, factors affecting sports performance were novelty seeking and persistence. Novelty seeking mainly seen in elite athletes has also been found to have an effect on sports performance score of elite athletes.[69] Persistence also affected sports performance of elite physical education students. The high persistence possessed by talented people in various fields proved that elite physical education students could achieve both academic and sports performances effectively.[75,82-84] Characteristic and temperamental factors that mediated academic performance of elite students with physical education major needed to be explained separately from sports performance and academic performance. Results suggest that it is necessary to have both opposite personality and temperamental factors to achieve sports performance and academic performance at the same time.

The current study has several limitations. First, the number of elite sports students was relatively small, which prevented generalization of the results. Further studies with a larger sample size are needed to identify the characteristics of elite athletes in the future. Second, few studies have investigated the relationship between TCI and smartphone apps. Therefore, additional research is needed to investigate the relationship between academic performance, TCI, and smartphone usage behavior by considering various academic backgrounds and age groups, including college students and athletes. Third, the academic performance criteria used in this study were the previous year's grade point average. Since the time of receiving grade preceded the time of using the app, it was difficult to conclude that the use of app had a direct effect on grades. Readers should consider it when interpreting results of this study. The classification of smartphone apps was arbitrary. Follow-up research must use academic performance standards and smartphone app classification standards that are more suitable for students majoring in sports and studying both practical and theoretical aspects.

In conclusion, elite sports students with high academic performance showed higher novelty seeking, reward dependence, persistence, self-directedness, and self-transcendence compared to general students. Therefore, the temperament and personality characteristics

of students represented by the TCI can predict their efforts and attitudes toward academic performance. In addition, temperament and characteristics were associated with smartphone app use pattern which could predict elite students. We can cautiously speculate that this personality trait is a prerequisite for becoming elite sports majors with the characteristics of both athletes and students.

SUPPLEMENTARY MATERIAL

Supplementary Table 1
Result of factor analysis

Click here to view

REFERENCES

1. Jameel RS, Jasim AH. Assessment of smart phone usage among colleges students at Al-Anbar University. *Ann Rom Soc Cell Biol* 2021;25(6):14059-68.

2. Tran J, Tran R, White JR Jr. Smartphone-based glucose monitors and applications in the management of diabetes: an overview of 10 salient "apps" and a novel smartphone-connected blood glucose monitor. *Clin Diabetes* 2012;30(4):173-8.
   CROSSREF

3. Helding L. Digital natives and digital immigrants: teaching and learning in the digital age. *J Sing* 2011;68(2):199-206.

4. Lepp A, Barkley JE, Sanders GJ, Rebold M, Gates P. The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *Int J Behav Nutr Phys Act* 2013;10(1):79.
   PUBMED | CROSSREF

5. Abi-Jaoude E, Naylor KT, Pignatiello A. Smartphones, social media use and youth mental health. *CMAJ* 2020;192(6):E136-41.
   PUBMED | CROSSREF

6. Chotpitayasunondh V, Douglas KM. How "phubbing" becomes the norm: the antecedents and consequences of snubbing via smartphone. *Comput Human Behav* 2016;63:9-18.
   CROSSREF

7. Kocyigit S, Guzel HS, Acikel B, Cetinkaya M. Comparison of smartphone addiction level, temperament and character and parental attitudes of adolescents with and without attention deficit hyperactivity disorder. *Int J Ment Health Addict* 2021;19(4):1372-84.
   CROSSREF

8. Ellis DA, Davidson BI, Shaw H, Geyer K. Do smartphone usage scales predict behavior? *Int J Hum Comput Stud* 2019;130:86-92.
   CROSSREF

9. Giunchiglia F, Zeni M, Gobbi E, Bignotti E, Bison I. Mobile social media usage and academic performance. *Comput Human Behav* 2018;82:177-85.
   CROSSREF

10. Troll ES, Friese M, Loschelder DD. How students' self-control and smartphone-use explain their academic performance. *Comput Human Behav* 2021;117:106624.
    CROSSREF

11. Ahmed RR, Salman F, Malik SA, Štreimikienė D, Soomro RH, Pahi MH. Smartphone use and academic performance of university students: a mediation and moderation analysis. *Sustainability* 2020;12(1):439.
    CROSSREF

12. King RC, Dong S. The impact of smartphone on young adults. *Bus Manag Rev* 2017;8(4):342-9.

13. Lee JW, Nam JJ, Kang KD, Han DH. The effect of smartphone app-use patterns on the performance of professional golfers. *Front Psychol* 2021;12:678691.
    PUBMED

14. Fortes LS, Lima-Junior D, Nascimento-Júnior JR, Costa EC, Matta MO, Ferreira ME. Effect of exposure time to smartphone apps on passing decision-making in male soccer athletes. *Psychol Sport Exerc* 2019;44:35-41.
   CROSSREF

15. Hayes M. *Social Media Usage Among Elite Athletes: An Exploration of Athlete Usage During Major Events [Doctoral Dissertation]*. Brisbane: Griffith University; 2019.

16. Smith LR, Sanderson J. I'm going to Instagram it! An analysis of athlete self-presentation on Instagram. *J Broadcast Electron Media* 2015;59(2):342-58.
   CROSSREF

17. Lee H, Ahn H, Nguyen TG, Choi SW, Kim DJ. Comparing the self-report and measured smartphone usage of college students: a pilot study. *Psychiatry Investig* 2017;14(2):198-204.
   PUBMED | CROSSREF

18. Lee PH, Tse AC, Wu CS, Mak YW, Lee U. Validation of self-reported smartphone usage against objectively-measured smartphone usage in Hong Kong Chinese adolescents and young adults. *Psychiatry Investig* 2021;18(2):95-100.
   PUBMED | CROSSREF

19. Lin YH, Wong BY, Lin SH, Chiu YC, Pan YC, Lee YH. Development of a mobile application (app) to delineate "digital chronotype" and the effects of delayed chronotype by bedtime smartphone use. *J Psychiatr Res* 2019;110:9-15.
   PUBMED | CROSSREF

20. Zimmermann L. "Your screen-time app is keeping track": consumers are happy to monitor but unlikely to reduce smartphone usage. *J Assoc Consum Res* 2021;6(3):377-82.
   CROSSREF

21. Hodes LN, Thomas KG. Smartphone screen time: inaccuracy of self-reports and influence of psychological and contextual factors. *Comput Human Behav* 2021;115:106616.
   CROSSREF

22. Ohme J, Araujo T, de Vreese CH, Piotrowski JT. Mobile data donations: Assessing self-report accuracy and sample biases with the iOS Screen Time function. *Mob Media Commun* 2021;9(2):293-313.
   CROSSREF

23. Bouwman H, de Reuver M, Heerschap N, Verkasalo H. Opportunities and problems with automated data collection via smartphones. *Mob Media Commun* 2013;1(1):63-8.
   CROSSREF

24. Wang W, Harari GM, Wang R, Müller SR, Mirjafari S, Masaba K, et al. Sensing behavioral change over time: using within-person variability features from mobile sensing to predict personality traits. *Proc ACM Interact Mob Wearable Ubiquitous Technol* 2018;2(3):1-21.

25. Rosenthal SR, Zhou J, Booth ST. Association between mobile phone screen time and depressive symptoms among college students: a threshold effect. *Hum Behav Emerg Technol* 2021;3(3):432-40.
   CROSSREF

26. Lauricella AR, Wartella E, Rideout VJ. Young children's screen time: the complex role of parent and child factors. *J Appl Dev Psychol* 2015;36:11-7.
   CROSSREF

27. Lane W, Manner C. The impact of personality traits on smartphone ownership and use. *Int J Bus Soc Sci* 2011;2(17):22-8.

28. Marciano L, Schulz PJ, Camerini AL. How smartphone use becomes problematic: application of the ALT-SR model to study the predicting role of personality traits. *Comput Human Behav* 2021;119:106731.
   CROSSREF

29. Peterka-Bonetta J, Sindermann C, Elhai JD, Montag C. Personality associations with smartphone and internet use disorder: a comparison study including links to impulsivity and social anxiety. *Front Public Health* 2019;7:127.
   PUBMED | CROSSREF

30. Rüegger D, Stieger M, Nißen M, Allemand M, Fleisch E, Kowatsch T. How are personality states associated with smartphone data? *Eur J Pers* 2020;34(5):687-713.
   CROSSREF

31. Stachl C, Hilbert S, Au JQ, Buschek D, De Luca A, Bischl B, et al. Personality traits predict smartphone usage. *Eur J Pers* 2017;31(6):701-22.
   CROSSREF

32. Beierle F, Probst T, Allemand M, Zimmermann J, Pryss R, Neff P, et al. Frequency and duration of daily smartphone usage in relation to personality traits. *Digit Psychol* 2020;1(1):20-8.
   CROSSREF

33. Stachl C, Au Q, Schoedel R, Gosling SD, Harari GM, Buschek D, et al. Predicting personality from patterns of behavior collected with smartphones. *Proc Natl Acad Sci U S A* 2020;117(30):17680-7.
PUBMED | CROSSREF

34. de Montjoye YA, Quoidbach J, Robic F, Pentland A. Predicting personality using novel mobile phone-based metrics. In: Greenberg AM, Kennedy WG, Bos ND, editors. *Proceedings of the 6th International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction*; 2013 April 2–5; Washington, DC, USA. Cham, Switzerland: Springer Nature; 2013, 48-55.

35. Xu R, Frey RM, Fleisch E, Ilic A. Understanding the impact of personality traits on mobile app adoption–Insights from a large-scale field study. *Comput Human Behav* 2016;62:244-56.
CROSSREF

36. Harari GM, Müller SR, Stachl C, Wang R, Wang W, Bühner M, et al. Sensing sociability: Individual differences in young adults' conversation, calling, texting, and app use behaviors in daily life. *J Pers Soc Psychol* 2020;119(1):204-28.
PUBMED | CROSSREF

37. Schoedel R, Pargent F, Au Q, Völkel ST, Schuwerk T, Bühner M, et al. To challenge the morning lark and the night owl: using smartphone sensing data to investigate day–night behaviour patterns. *Eur J Pers* 2020;34(5):733-52.
CROSSREF

38. Hanafi E, Siste K, Wiguna T, Kusumadewi I, Nasrun MW. Temperament profile and its association with the vulnerability to smartphone addiction of medical students in Indonesia. *PLoS One* 2019;14(7):e0212244.
PUBMED | CROSSREF

39. Zeidan J, Hallit S, Akel M, Louragli I, Obeid S. Problematic smartphone use and affective temperaments among Lebanese young adults: scale validation and mediating role of self-esteem. *BMC Psychol* 2021;9(1):136.
PUBMED | CROSSREF

40. Lee HW, Choi JS, Shin YC, Lee JY, Jung HY, Kwon JS. Impulsivity in internet addiction: a comparison with pathological gambling. *Cyberpsychol Behav Soc Netw* 2012;15(7):373-7.
PUBMED | CROSSREF

41. Reynolds B, Ortengren A, Richards JB, De Wit H. Dimensions of impulsive behavior: personality and behavioral measures. *Pers Individ Dif* 2006;40(2):305-15.
CROSSREF

42. Walther B, Morgenstern M, Hanewinkel R. Co-occurrence of addictive behaviours: personality factors related to substance use, gambling and computer gaming. *Eur Addict Res* 2012;18(4):167-74.
PUBMED | CROSSREF

43. Olivencia-Carrión MA, Ferri-García R, Rueda MD, Jiménez-Torres MG, López-Torrecillas F. Temperament and characteristics related to nomophobia. *Psychiatry Res* 2018;266:5-10.
PUBMED | CROSSREF

44. Aka BT, Kalecik S, Doğruyol B. Psychological factors related to problematic internet and smartphone use. *Nesne Dergisi* 2020;8(16):1-15.
CROSSREF

45. Vedel A. The Big Five and tertiary academic performance: a systematic review and meta-analysis. *Pers Individ Dif* 2014;71:66-76.
CROSSREF

46. Bhagat V, Nayak RD. Neuroticism and academic performance of medical students. *Int J Humanit Soc Sci Invent* 2014;3(1):51-5.

47. Ciorbea I, Pasarica F. The study of the relationship between personality and academic performance. *Procedia Soc Behav Sci* 2013;78:400-4.
CROSSREF

48. Rosander P, Bäckström M. Personality traits measured at baseline can predict academic performance in upper secondary school three years late. *Scand J Psychol* 2014;55(6):611-8.
PUBMED | CROSSREF

49. Embalzado HT, Varma P. Influences of temperament types on university students' well-being, academic performance and college adjustment. Scholar. *Hum Sci* 2018;9(2):186-202.

50. Haverkamp BF, Wiersma R, Vertessen K, van Ewijk H, Oosterlaan J, Hartman E. Effects of physical activity interventions on cognitive outcomes and academic performance in adolescents and young adults: a meta-analysis. *J Sports Sci* 2020;38(23):2637-60.
PUBMED | CROSSREF

51. Bailey R, Armour K, Kirk D, Jess M, Pickup I, Sandford R, et al. The educational benefits claimed for physical education and school sport: an academic review. *Res Pap Educ* 2009;24(1):1-27.
CROSSREF

52. Wilson KE, Dishman RK. Personality and physical activity: a systematic review and meta-analysis. *Pers Individ Dif* 2015;72:230-42.
    CROSSREF

53. Cloninger CR, Przybeck TR, Svrakic DM, Wetzel RD. *The Temperament and Character Inventory (TCI): A Guide to Its Development and Use*. Seattle, WA, USA: Center for Psychobiology of Personality, Washington University; 1994.

54. Shakoor F, Fakhar A, Abbas J. Impact of smartphones usage on the learning behaviour and academic performance of students: empirical evidence from Pakistan. *Int J Acad Res Bus Soc Sci* 2021;11(2):862-81.
    CROSSREF

55. Sunday OJ, Adesope OO, Maarhuis PL. The effects of smartphone addiction on learning: a meta-analysis. *Comput Hum Behav* 2021;4:100114.
    CROSSREF

56. Xu Q, Erman J, Gerber A, Mao Z, Pang J, Venkataraman S. Identifying diverse usage behaviors of smartphone apps. In: *Proceedings of the 2011 ACM SIGCOMM Conference on Internet Measurement Conference*; 2011 November 2-4; Berlin, Germany. New York, NY, USA: Association for Computing Machinery; 2011, 329-44.

57. Agustini D, Bergamini MF, Marcolino-Junior LH. Tear glucose detection combining microfluidic thread based device, amperometric biosensor and microflow injection analysis. *Biosens Bioelectron* 2017;98:161-7.
    PUBMED | **CROSSREF**

58. Douglas KH, Uphold NM. iPad® or iPod touch®: Evaluating self-created electronic photographic activity schedules and student preferences. *J Spec Educ Technol* 2014;29(3):1-14.
    CROSSREF

59. Jesse GR. Smartphone and app usage among college students: using smartphones effectively for social and educational needs. In: *Proceedings of the EDSIG Conference*; 2015 November 1–4; Wilmington, NC, USA. Wilmington, NC, USA: ISCAP; 2015.

60. Bae SJ, Hong SY. Association between the learning styles with personalities of medical students and their clinical performance examination achievements. *Int J Internet Broadcast Commun* 2021;13(1):219-28.
    CROSSREF

61. Cloninger CR, Svrakic DM, Przybeck TR. A psychobiological model of temperament and character. *Arch Gen Psychiatry* 1993;50(12):975-90.
    PUBMED | **CROSSREF**

62. Choi Y, Yang J, Jin S. A study on the temperament and character of the gifted in invention on the basis of latent profile analysis. *J Creat Inf Cult* 2019;5(2):117-34.

63. Kim IH, Ko E, Kim EJ, Ban SH, Jung JJ, Lee SH, et al. Effects of temperament and character on the specialty interests of medical students. *Korean J Biol Psychiatry* 2012;19(4):199-204.

64. Lee K, Chung H. Testing construct equivalence of TCI using multi group confirmatory factor analysis. *CNU J Educ Stud* 2013;34(2):57-77.
    CROSSREF

65. Rettew DC, Stanger C, McKee L, Doyle A, Hudziak JJ. Interactions between child and parent temperament and child behavior problems. *Compr Psychiatry* 2006;47(5):412-20.
    PUBMED | **CROSSREF**

66. Cloninger CR, Przybeck TR, Svrakic DM. The tridimensional personality questionnaire: US normative data. *Psychol Rep* 1991;69(3 Pt 1):1047-57.
    PUBMED | **CROSSREF**

67. Allport GW. The open system in personality theory. *J Abnorm Soc Psychol* 1960;61(3):301-10.
    PUBMED | **CROSSREF**

68. Cattell RB, Rao DC, Schuerger JM, Vaughan DS. Unitary personality source traits analyzed for heritability. *Hum Hered* 1981;31(5):261-75.
    PUBMED | **CROSSREF**

69. Eysenck HJ. The effects of psychotherapy: an evaluation. *J Consult Psychol* 1952;16(5):319-24.
    PUBMED | **CROSSREF**

70. Cloninger CR, Zohar AH. Personality and the perception of health and happiness. *J Affect Disord* 2011;128(1-2):24-32.
    PUBMED | **CROSSREF**

71. Cohen J. A power primer. *Psychol Bull* 1992;112(1):155-9.
    PUBMED | **CROSSREF**

72. World Medical Association. *WMA Declaration of Helsinki—Ethical Principles for Medical Research Involving Human Subjects (July 9, 2018)*. Ferney-Voltaire, France: World Medical Association; 2019.

73. Moreira P, Pedras S, Pombo P. Students' personality contributes more to academic performance than well-being and learning approach-implications for sustainable development and education. *Eur J Investig Health Psychol Educ* 2020;10(4):1132-49.
   PUBMED | CROSSREF

74. Hancock MG, Greenwell TC. The selection of a sport management major: factors influencing student choice from a consumer-oriented perspective. *Sport Manag Educ J* 2013;7(1):13-24.
   CROSSREF

75. Liu CL, Yin XW. Effects of extracurricular physical exercising on the physical pride and sense of life satisfaction of sport backward college students. *J Phys Educ* 2010;17:46-9.

76. Cross JL, Fouke BW. Redefining the scholar-athlete. *Front Sports Act Living* 2019;1:10.
   PUBMED | CROSSREF

77. DeLuca JR, Braunstein-Minkove J. An evaluation of sport management student preparedness: recommendations for adapting curriculum to meet industry needs. *Sport Manag Educ J* 2016;10(1):1-12.
   CROSSREF

78. Han DH, Kim JH, Lee YS, Bae SJ, Bae SJ, Kim HJ, et al. Influence of temperament and anxiety on athletic performance. *J Sports Sci Med* 2006;5(3):381-9.
   PUBMED

79. Kang KD, Han DH, Hannon JC, Hall MS, Choi JW. Temperamental predictive factors for success in Korean professional baseball players. *Psychiatry Investig* 2015;12(4):459-65.
   PUBMED | CROSSREF

80. Lee HG. The experience process of the student-athletes who perform both study and sport: redefining self. *Korean J Sociol Sport* 2011;24(1):1-24.
   CROSSREF

81. Monasterio E, Mei-Dan O, Hackney AC, Lane AR, Zwir I, Rozsa S, et al. Stress reactivity and personality in extreme sport athletes: the psychobiology of BASE jumpers. *Physiol Behav* 2016;167:289-97.
   PUBMED | CROSSREF

82. van Breda K, Collins M, Stein DJ, Rauch L. The COMT val[158]met polymorphism in ultra-endurance athletes. *Physiol Behav* 2015;151:279-83.
   PUBMED | CROSSREF

83. Kang S. A study on differences of career barriers, employment stress and career development behavior among collegiate athletes, sport-majored college students and non-sport-majored college students. *Korean J Phys Educ* 2015;54(1):83-95.

84. Davis KD, Winsler A, Middleton M. Students' perceptions of rewards for academic performance by parents and teachers: relations with achievement and motivation in college. *J Genet Psychol* 2006;167(2):211-20.
   PUBMED | CROSSREF

85. Moreira PA, Oliveira JT, Cloninger KM, Azevedo C, Sousa A, Castro J, et al. The psychometrics and validity of the Junior Temperament and Character Inventory in Portuguese adolescents. *Compr Psychiatry* 2012;53(8):1227-36.
   PUBMED | CROSSREF

86. Bauger L, Eisemann M, Vangberg HC. Personality traits among junior elite athletes in Norway, and a comparison with their non-athletic counterparts. *Athl Insight* 2013;5(2):145.

87. Nixon SJ, Parsons OA. Cloninger's tridimensional theory of personality: construct validity in a sample of college students. *Pers Individ Dif* 1989;10(12):1261-7.
   CROSSREF

88. Singh K. Study of achievement motivation in relation to academic achievement of students. *Int J Educ Plann Adm* 2011;1(2):161-71.

89. Lichtenberg P, Bachner-Melman R, Ebstein RP, Crawford HJ. Hypnotic susceptibility: multidimensional relationships with Cloninger's Tridimensional Personality Questionnaire, COMT polymorphisms, absorption, and attentional characteristics. *Int J Clin Exp Hypn* 2004;52(1):47-72.
   PUBMED | CROSSREF

90. Brecht AA, Burnett DD. Advising student-athletes for success: predicting the academic success and persistence of collegiate student-athletes. *NACADA J* 2019;39(1):49-59.
   CROSSREF

91. Nasvytienė D, Lazdauskas T. Temperament and academic achievement in children: a meta-analysis. *Eur J Investig Health Psychol Educ* 2021;11(3):736-57.
   CROSSREF

92. Ali M, Yaacob RA, Endut MN, Langove NU. Strengthening the academic usage of social media: an exploratory study. *J King Saud Univ Comput Inf Sci* 2017;29(4):553-61.
   CROSSREF

93. Karpinski AC, Kirschner PA, Ozer I, Mellott JA, Ochwo P. An exploration of social networking site use, multitasking, and academic performance among United States and European university students. *Comput Human Behav* 2013;29(3):1182-92.
CROSSREF

94. González-Cutre D, Sicilia Á. The importance of novelty satisfaction for multiple positive outcomes in physical education. *Eur Phys Educ Rev* 2019;25(3):859-75.
CROSSREF

95. Wang JJ, Wann DL, Lu Z, Zhang JJ. Self-expression through sport participation: exploring participant desired self-image. *Eur Sport Manag Q* 2018;18(5):583-606.
CROSSREF

96. Moghavvemi S, Sulaiman A, Aziz AA, Wai PS. The impact of Facebook usage on academic performance. In: *Proceedings of the International Conference on Research and Innovation in Information Systems (ICRIIS)*; 2017 July 16–17; Langkawi, Malaysia. Manhattan, NY, USA: IEEE; 2017.

97. Shahibi MS, Rusli K. The influence of internet usage on student's academic performance. *Int J Acad Res Bus Soc Sci* 2017;7(8):873-87.
CROSSREF

98. Soegoto E, Tjokroadiponto S. Effect of internet on student's academic performance and social life. *IOP Conf Ser Mater Sci Eng* 2018;407:012176.

99. Driller M, Tavares F, McMaster D, O'Donnell S. Assessing a smartphone application to measure counter-movement jumps in recreational athletes. *Int J Sports Sci Coaching* 2017;12(5):661-4.
CROSSREF

100. Roos F, Surujlal J. Video analysis in golf coaching: an insider perspective. *Mediterr J Soc Sci* 2014;5(21):399.
CROSSREF

101. Sheehan RB, Herring MP, Campbell MJ. Longitudinal relations of mental health and motivation among elite student-athletes across a condensed season: plausible influence of academic and athletic schedule. *Psychol Sport Exerc* 2018;37:146-52.
CROSSREF

102. Voight M, Page P, Chidester M, Hardiek L, Macko S, Sexton Z, et al. The impact of hip abduction elastic-resisted neuromuscular feedback on frontal plane knee kinematics in female volleyball athletes. *J Perform Health Res* 2017;1(2):23-30.

103. Johannes N, Veling H, Verwijmeren T, Buijzen M. Hard to resist? *J Media Psychol* 2019;31(4):214-25.
CROSSREF

104. Thornton B, Faires A, Robbins M, Rollins E. The mere presence of a cell phone may be distracting. *Soc Psychol (Gott)* 2014;45(6):479-88.
CROSSREF

105. Duckworth AL, Taxer JL, Eskreis-Winkler L, Galla BM, Gross JJ. Self-control and academic achievement. *Annu Rev Psychol* 2019;70(1):373-99.
PUBMED | **CROSSREF**

106. Han S, Yi YJ. How does the smartphone usage of college students affect academic performance? *J Comput Assist Learn* 2019;35(1):13-22.
CROSSREF

107. Lane HY, Chang CJ, Huang CL, Chang YH. An investigation into smartphone addiction with personality and sleep quality among university students. *Int J Environ Res Public Health* 2021;18(14):7588.
PUBMED | **CROSSREF**

108. Michaels JW. Classroom reward structures and academic performance. *Rev Educ Res* 1977;47(1):87-98.
CROSSREF

109. Çakıroğlu Ü, Başıbüyük B, Güler M, Atabay M, Memiş BY. Gamifying an ICT course: influences on engagement and academic performance. *Comput Human Behav* 2017;69:98-107.
CROSSREF

110. Camilleri AC, Camilleri MA. Mobile learning via educational apps: an interpretative study. In: *Proceedings of the 2019 5th International Conference on Education and Training Technologies*; 2019 May 27–29; Seoul, Korea. New York, NY, USA: Association for Computing Machinery; 2019.

111. Fuster-Guilló A, Pertegal-Felices ML, Jimeno-Morenilla A, Azorín-López J, Rico-Soliveres ML, Restrepo-Calle F. Evaluating impact on motivation and academic performance of a game-based learning experience using kahoot. *Front Psychol* 2019;10:2843.
PUBMED | **CROSSREF**

112. Garneli V, Giannakos M, Chorianopoulos K. Serious games as a malleable learning medium: the effects of narrative, gameplay, and making on students' performance and attitudes. *Br J Educ Technol* 2017;48(3):842-59.
CROSSREF

113. Sawant S, Lodhe N. Digital wellbeing. *VIVA Tech Int J Res Innov* 2021;1(4):1-4.
PUBMED

114. Haugan G, Moksnes UK, Løhre A. Intrapersonal self-transcendence, meaning-in-life and nurse-patient interaction: powerful assets for quality of life in cognitively intact nursing-home patients. *Scand J Caring Sci* 2016;30(4):790-801.
PUBMED | CROSSREF

115. Wright KB. *Quality of Life, Self-Transcendence, Illness Distress, and Fatigue in Liver Transplant Recipients.* Austin, TX, USA: The University of Texas at Austin; 2003.

116. Halson SL. Sleep monitoring in athletes: motivation, methods, miscalculations and why it matters. *Sports Med* 2019;49(10):1487-97.
PUBMED | CROSSREF

117. Kettunen E, Kari T, Makkonen M, Critchley W. Digital coaching and athlete's self-efficacy: a quantitative study on sport and wellness technology. In: *Proceedings of the Mediterranean Conference on Information Systems*; 2018 September 28–30; Corfu, Greece. [place unknown]: AISeL; 2018.

118. Reed PG. Self-transcendence and mental health in oldest-old adults. *Nurs Res* 1991;40(1):5-11.
PUBMED | CROSSREF