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Cross-lagged relationships between problematic Internet use and lifestyle changes

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ABSTRACT

Cross-lagged analysis of panel survey data collected from Taiwanese college students (initially 387 males and 370 females) was used to examine the temporal relationship between problematic Internet use (PIU) and lifestyle changes during the first year in college. We hypothesized that a reciprocal relationship might exist between PIU and lifestyle changes. Structural equation modeling was adopted to test several nested cross-lagged relationship models. The results showed that four measures of lifestyle changes and PIU were moderately to highly stable across one year. Moreover, PIU in freshman year predicted negative changes in lifestyle in the following year, including a reduction of physical and social activities, irregular diet and unhealthy sleep. Lifestyle changes in freshman year, in contrast, did not predict PIU in sophomore year; the hypothesized reciprocal relationship between PIU and lifestyle changes was not warranted. Implications and limitations are discussed.

1. Introduction

Problematic Internet use (PIU, also known as pathological Internet use or Internet addiction) is an issue of great concern in Taiwan, a country where more than 1.3 million college students comprise 5.8% of the total population (Ministry of Education, 2011). A significant percentage of these students, 15%, estimated by Lin, Ko, and Wu (2011), could possibly face challenges in managing their Internet usage at some point during their college careers (also see Chou, Condron, & Belland, 2005). Considerable efforts have been made to include "internet addiction" or its derivatives in the Diagnostic and Statistical Manual version V (e.g., O'Brien, 2011). This sort of neurobehavioral addictive disorder does not involve a chemical substance but otherwise shares many characteristics of substance dependency; some researchers (e.g., Shapira et al., 2003; Young, 1998) have also suggested that this disorder is relevant to impulse control disorder. However, no decisions have been made as to the final form of the "addiction and related disorders section" in DSM-V. At this time, "Internet addiction" is recommended for further study prior to inclusion in the DSM-V. Therefore, emphasis has been placed on the diagnosis, treatment and prevention of PIU, especially among those most at risk.

PIU in this study follows the Internet addiction definition proposed by Young (1996, 1998) and Ko, Yen, Chen, Chen, and Yen (2005), indicating that users shows symptoms of addiction and impulse control disorder in DSM-IV-TR, such as: impulse Internet use, impairment of control, tolerance, and withdrawal symptoms. Previous studies (Aboujaoude, 2010; Heise, 1975) have suggested that PIU leads to neglect of school study, work, family and other social responsibilities. Because the majority of college students live away from home with minimal parental monitoring and easy access to the Internet, they are more vulnerable to PIU than adults (Ha et al., 2007). It has been observed that the initial emergence of PIU alters college students' daily routines, including changes in their patterns of diet, sleep, physical, and interpersonal activities (Lin et al., 2011). More specifically, students displaying PIU had delayed meals/unhealthy diet and sedentary habits, were late to bed, slept irregularly and were inactive in significant relationships. For some students, this inactive lifestyle, stemming from excessive Internet use, gradually developed into major functional impairments (e.g., jeopardizing or losing a significant relationship, educational or career opportunity) during the college years (Fortson, Scotti, Chen, Malone, & Del Ben, 2007). Many researchers (Ko et al., 2005; Shapira et al., 2003; Young, 1998) have suggested functional impairments (conceptually close to our unhealthy lifestyle changes definition which is of a less acute level of impairment) as the required criteria for Internet addiction diagnosis.

Due to the unknown temporal order of function impairment and PIU, it is imperative to conduct more research on the relationship between them. Therefore, the present paper addresses the issue of determining a temporal relationship between PIU and

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various daily life functions. In this study, a cross-lagged analysis was adopted due to the potential ability to identify the direction of influence between them.

2. Theoretical background

Lifestyle is a distinctive manner of living defined by a set of manifest and patterned behaviors in individuals consistently appearing over a period of time (Coulson, Eiser, & Eiser, 1997). In health promotion theory and practice, lifestyle is a key concept in the development of a socially based health model. Lifestyle is associated with health-risk factors at the individual level (e.g., diet, drinking, exercise level, and smoking) and with preventive medicine or health promotion at the population level. Coulson et al. (1997) noted that both health-damaging and health-enhancing behaviors are focuses of research in lifestyle and health. The literature suggests that a healthy lifestyle reduces the possibility of being sick and keeps people physically and mentally healthy (Chiuve, McCullough, Sacks, & Rimm, 2006; Hu et al., 2001).

The effectiveness of PIU prevention programs for college students mostly depends on the degree to which college students take responsibility for their own mental health. Such responsibility includes the following: avoiding health risks, such as excessive Internet use, getting adequate rest and exercise, keeping regular dietary habits, successfully managing stress, and maintaining a positive outlook on life. Young (2007) has suggested that, as part of behavioral therapy, counselors help Internet addicts to develop positive lifestyle changes to replace the portion of their life previously occupied by the Internet. Although not explicitly mentioned, there is an assumption that healthier lifestyle changes reduce PIU, at least according to this therapy.

Adolescents have been found to be more at risk for PIU than adults, and adolescents' lifestyles are easily affected by excessive use of the Internet (Ha et al., 2007). Some research with adolescents suggests that the formation of PIU might lead to adverse consequences and changes in lifestyle, including physical inactivity (Yen et al., 2010), extended time spent on the Internet, increased use of alcohol and tobacco, short duration/lack of sleep (Choi et al., 2009; Douglas et al., 2008), and irregular dietary habits/poor eating patterns (Choi et al., 2009; Kim & Chun, 2005; Kim et al., 2010). Kim and Chun (2005) found that Internet addicts, screened from Korean adolescents, are more likely to report poor diet, less sleep, and less regular exercise than non-addicts. Excessive daytime sleep was also found to be a common problem for Internet addicts (Choi et al., 2009) in a sample of Korean adolescents.

3. The present study

According to the aforementioned literature, associations exist between PIU and lifestyle changes, such as loss of sleep, irregular and unhealthy diet, and fewer physical and social activities (Choi et al., 2009). However, these studies were based on cross-sectional data, and thus, did not address the temporal relationship between PIU and lifestyle changes. Clarification of the temporal relationship between PIU and lifestyle would provide a complete picture for college counseling and health centers to establish effective primary prevention programs. Some researchers (Douglas et al., 2008; Ho & Lee, 2001) suggest that PIU leads to an unhealthy lifestyle, but no rigorous analysis or evidence of order has been provided. In fact, it is quite possible that more (or less) healthy lifestyles lead to less (or more) PIU. Behavioral therapists have adopted this logic in the treatment of Internet addicts and promote healthy lifestyles to reduce PIU symptoms (Young, 2007). True experiments are required to decisively answer questions about causal relationships (Cook, Campbell, & Day, 1979) but are probably impossible to conduct. Consequently, longitudinal studies in which both PIU and lifestyle are repeatedly measured across time are recommended for the identification of temporal order effects.

The objective of the present study was to investigate cross-lagged relationships between PIU and lifestyle changes among Taiwanese college students using structural equation modeling (SEM). The cross-lagged associations may be unidirectional (i.e., lifestyle changes leading to PIU or PIU leading to lifestyle changes) or reciprocal (i.e., lifestyle changes and PIU affecting each other). Our hypotheses proposed that a reciprocal relationship might exist between PIU and lifestyle changes based on previous research outcomes and inferences from their suggestions (Kim et al., 2010; Young, 2007).

Cross-lagged analysis is a methodology used to detect possible causal relationships between latent (or observed) variables (Heise, 1975). Relationships among multiple variables are examined and several causal models are compared to determine which model

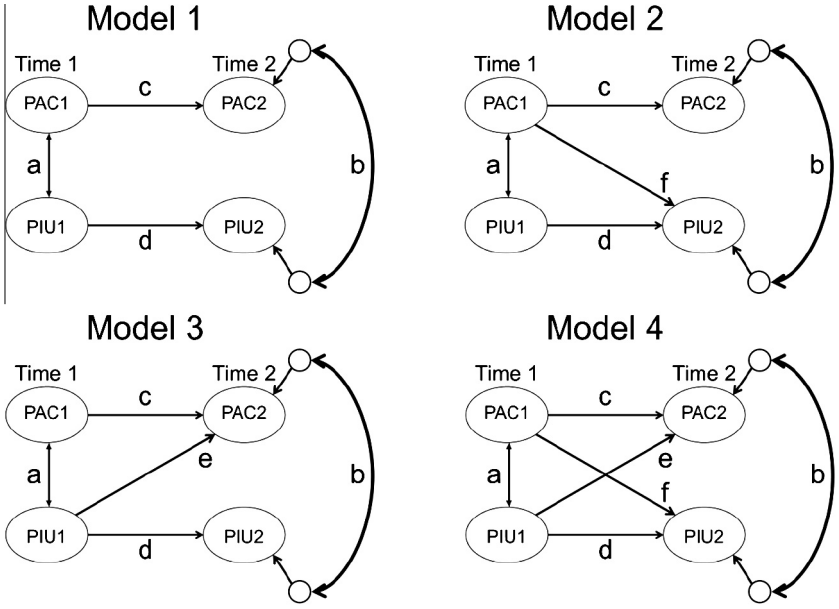

Fig. 1. Generic model for the cross-lagged design.

best fit the data. The temporal effect (i.e., the delay or stability effect) of the same variable is taken into account to control the influence on the subsequent variable. Moreover, within a SEM framework, correlation between two variables can be elaborately setup as two single directions, which permits unequal influence on another variable. Cross-lagged relationships are assessed by comparing covariation between two variables measured at two time points. To exclude changes or differences in covariance due to measurement error, factor analysis techniques are commonly used, and the cross-lagged relationship is then examined on the latent level. However, this analysis requires that constructs are measured in the same way at different time-points. To ensure that this is the case, measurement invariance (MI) should be examined (see Meredith, 1993). Fig. 1 demonstrates four generic models tested in this study using physical activity change (PAC) as an example of a distinct lifestyle change factor (each of three other lifestyle factors could replace PAC in Fig. 1).

The participants in this study included typical college students who use the Internet, not merely users who already show severe Internet dependency symptoms. Specific research questions of interest included the following:

(1) Does PIU predict subsequent lifestyle changes (physical activity, social activity, dietary pattern and sleep pattern change)?
(2) Do lifestyle changes predict subsequent PIU?
(3) Do PIU and lifestyle changes show a reciprocal relationship?

4. Methods

4.1. Participants

Participants were drawn from the list of college respondents of a 2009 to 2011 NetYouth and adolescent well-being longitudinal survey funded by the National Science Council of the Republic of China (ROC, Taiwan) to the fourth author. The participants received a small gift as the compensation. All participants were freshmen at the first round of data collection (Time 1, $n = 757$; 387 males and 370 females), which took place in 2009. The second round of data collection took place one academic year later, when the same participants were sophomores (Time 2, $n = 647$; 316 males and 331 females).

4.2. Instruments

All participants completed several questionnaires regarding PIU, lifestyle, and demographic information. A questionnaire concerning lifestyle changes and PIU (LC-PIU, Yeh, Lin, Tseng, & Hwang, 2012) was administered at two points in time. The LC-PIU consisted of 23 Likert-style items ranging from 1 (never) to 5 (always) and measures five constructs, including physical activity change (PAC), social activity change (SAC), dietary pattern change (DPC), sleep pattern change (SPC), and problematic Internet use (PIU). The factor structure was confirmed with adequate confirmatory factor analysis (CFA) model fits, and the discriminate and convergent validity were acceptable (Yeh et al., 2012).

The PIU scale follows the Internet addiction definition proposed by Young (1996, 1998) and confirmed by Ko et al. (2005), indicating that Internet addiction shows symptoms of addiction and impulse control disorder in DSM-IV-TR. Our PIU scale (5 items) does not include negative consequences caused by excessive Internet use. PIU conveys four symptoms: impulse Internet use, impairment of control, tolerance, and withdrawal symptoms. "Whenever I use the Internet, I feel excited and satisfied" is a statement about impulsivity. "I have tried to spend less time online, but those attempts were in vain" and "Though I plan to use the internet for just a while, I stay online longer than originally intended" state the impairment of control. "When I tried to cut down or stop Internet use, I felt anxious" is regard to withdrawal symptom; while "I have to spend more time online in order to have the same level of satisfaction as I had when I just started to use the Internet" is about tolerance aspect.

PAC (5 items) concerns the extent to which Internet use changes the participants' daily physical routine. An example item states "I neglect exercise due to spending time online." SAC (5 items) concerns the changes in social activities and interactions resulting from Internet use (e.g., "I reduce face-to-face contact with others because of the Internet use"). DPC (5 items) investigates whether Internet use leads to changes in eating habits, with items such as "I spend time online such that I ignore regular meals and eat whatever is available." SPC (3 items) assesses whether PIU changes sleep patterns (e.g., "I have reversed sleep patterns because of the Internet use").

4.3. Statistical analysis

Fig. 1 presents four generic models tested in this study, using physical activity change (PAC) as an example of a distinct lifestyle change factor. For simplicity, the observed items loading on the corresponding latent variable are not presented in the diagram. Two latent variables, PAC and PIU, are measured at two time points. PAC1 is the measure of physical activity change at Time 1; likewise, PIU1 is problematic Internet use at Time 1. To investigate whether PIU predicts a distinct change of lifestyle, six possible relationships were examined within a cross-lagged analytic model. In Model 4 of Fig. 1, the "*a*" and "*b*" lines represent the synchronous correlations between different latent variables. PIU and PAC measured at the same time are presumed to be correlated, while the measurement errors associated with Time 1 latent variables are correlated to those associated with Time 2 latent variables. The auto-regressive coefficients "*c*" and "*d*," which are also indices of stability, represent the lagged relationships between the same latent variables over time and are expected to be significantly positive. The path coefficients "*e*" and "*f*," which represent the cross-lagged relationship between different latent variables, are of major research concern. The path coefficient "*e*" represents the temporal effect of prior PIU on later PAC, whereas the path coefficient "*f*" shows the reverse effect of previous PAC on later PIU.

For each lifestyle change, four nested models (Model 1 to Model 4) were evaluated and compared to identify which model provided the best fit to the data. Model 1 presumes significant auto-regressive relationships for both PIU and lifestyle changes but no lagged effects. Model 2 and Model 3 presume a single lagged relationship between PIU and lifestyle changes. Model 2 presumes that previous lifestyle changes have impacts on cross-time PIU, whereas Model 3 presumes that Time-1 PIU changes Time-2 lifestyle. Model 4 presumes a reciprocal relationship model where both PIU and lifestyle changes have lagged influences on each other. In step one, we compared Model 1 to Model 2 and Model 1 to Model 3. Compared with Model 1, if the chi-square value of Model 2 (or Model 3) was significantly reduced and if the cross-lagged path coefficient was significant, then we concluded that Model 2 (or Model 3) provided a better fit to the data than Model 1. In step two, we evaluated whether lifestyle changes and PIU demonstrated a reciprocal cross-lagged effect. The best-fit model from among Models 1, 2, and 3 was then compared with Model 4. If Model 4 showed a better fit than the model chosen in the first step, we then concluded that the relationship between lifestyle changes and PIU was reciprocal. We expected that Model 4, when compared with the other three models, would provide a good fit to the data and the best fit among our four models. In other words, we expected

that the relationships of PIU and four lifestyle changes to be reciprocal.

We used Mplus Version 6.11 (Muthén & Muthén, 2007) to conduct SEM analyses, and all parameters were estimated using the maximum likelihood robust (MLR) procedure. Missing data were evaluated using the full information maximum likelihood (FIML) estimation method. The criteria listed below were used to assess the model fit: (a) a comparative fit index (CFI) of more than 0.90 (Bentler, 1990); (b) a root mean squared error of approximation (RMSEA) of less than 0.08 and ideally less than 0.05, indicating a moderate fit (Steiger & Lind, 1980); and (c) a standardized root mean squared residual (SRMR) of less than 0.05, suggesting a good fit between the hypothesized model and the data (Bentler, 1995). Rather than using model fit indices, the Akaike Information Criterion (AIC) was used as an index of parsimony (Akaike, 1987), with smaller AIC values suggesting more parsimonious models.

5. Results

5.1. Measurement invariance

Before the test of Models 1 to 4, it was necessary to examine measurement invariance (MI)—whether latent constructs were measured in the same way on different occasions (Meredith, 1993). A series of model comparisons were used to test the extent to which measurements were invariant. The first step was to test whether the measurements were "configurally invariant," meaning the factors and the pattern of factor loadings were the same across two time points. Assuming that the model showed good fit to the data, then the construct was configurally invariant and treated as the baseline model for further tests. Second, factor loadings corresponding to the items were constrained to be equal across time to test the "weak factorial invariance." Third, we assigned equal constraints on the intercepts of the observed variables to test "strong factorial invariance" and, finally, on the error variance to test "strict factorial invariance." Previous research (Cheung & Rensvold, 2002) has suggested that a decrease in CFI of more than 0.1 would indicate the more constrained model demonstrates worse specification. Our results indicated that PIU and the four lifestyle measurements had invariant factorial structures at the two time points, for PIU: $\chi^2_{(29)} = 74.05$, CFI = 0.984, RMSEA = 0.045, SRMR = 0.028; for PAC: $\chi^2_{(29)} = 70.57$, CFI = 0.982, RMSEA = 0.044, SRMR = 0.026; for SAC: $\chi^2_{(29)} = 128.05$, CFI = 0.959, RMSEA = 0.067, SRMR = 0.033; for DPC: $\chi^2_{(29)} = 117.11$, CFI = 0.963, RMSEA = 0.063, SRMR = 0.041; and for SPC: $\chi^2_{(5)} = 16.80$, CFI = 0.993, RMSEA = 0.056, SRMR = 0.022. Across time, the measurement models of PIU, PAC, SAC, and DPC had equal factor loadings but not equal intercepts. Only sleep pattern change had both equal factor loadings and equal intercepts.

5.2. Descriptive statistics

Table 1 shows descriptive statistics, internal consistency and the interrelationship of PAC, SAC, DPC, SPC and PIU between Time 1 and Time 2. The results indicate adequate reliabilities for each subcomponent of the LC-PIU scale (Cronbach's αs ranged from 0.68 to 0.81; see Table 1 for details).

5.3. Test of PIU-LC models

We tested the fit of each PIU-LC model to the data. For the cross-year relationship of each lifestyle change (physical activity change, social activity change, diet pattern change, and sleep pattern change) with problematic Internet use, all four models exhibited acceptable fit to the data (RMSEA ranging from 0.038 to 0.052, CFI ranging from 0.955 to 0.968, and SRMR ranging from 0.034 to 0.045). To investigate which model fit the data best, a series of nested model comparisons was performed (see Table 2).

5.4. Model comparison for cross-lagged analysis

5.4.1. Physical activity change and problematic Internet use

For the PIU–PAC models shown in Table 2, Model 3 fit the data significantly better than Model 1 ($\Delta\chi^2 = 8.95$, $p < 0.01$). However, the chi-square difference between Model 3 and Model 4 was not significant ($\Delta\chi^2 = 0.66$, $p = 0.42$), indicating that Model 4 did not significantly improve the model specification. Model 3 yielded the lowest AIC values among the four models (AIC = 32073.14), indicating that Model 3 provided the best fit to the data and was the most parsimonious of the models examined. In Model 3, synchronous correlations between PAC and PIU were positive (Time 1 $a = 0.76$, Time 2 $b = 0.69$, $ps < 0.001$, in Table 3). The auto-regressive coefficients of PAC and PIU were significant (PAC: $c = 0.55$, PIU: $d = 0.70$, $ps < 0.001$), suggesting that measures of PAC and PIU were

Table 1
Descriptive statistics, internal consistency, and correlations among four lifestyle changes and PIU.

	Time 1					Time 2				
	PAC1	SAC1	DPC1	SPC1	PIU1	PAC2	SAC2	DPC2	SPC2	PIU2
Time 1										
PAC1	–									
SAC1	0.59	–								
DPC1	0.54	0.46	–							
SPC1	0.55	0.47	0.56	–						
PIU1	0.58	0.49	0.50	0.54	–					
Time 2										
PAC2	(0.63)	0.43	0.41	0.43	0.49	–				
SAC2	0.42	(0.54)	0.29	0.36	0.39	0.63	–			
DPC2	0.36	0.28	(0.57)	0.45	0.38	0.54	0.45	–		
SPC2	0.34	0.33	0.32	(0.54)	0.38	0.57	0.54	0.53	–	
PIU2	0.42	0.33	0.30	0.40	(0.61)	0.63	0.57	0.49	0.59	–
Mean	2.19	1.50	2.12	1.93	1.83	2.11	1.53	2.07	1.91	1.82
SD	0.70	0.54	0.67	0.78	0.64	0.69	0.53	0.63	0.76	0.64
Items	5	5	5	3	5	5	5	5	3	5
Alpha	0.74	0.78	0.75	0.76	0.78	0.77	0.79	0.76	0.68	0.81

Note: All coefficients were significant at $p < 0.01$, PAC = physical activity change, SAC = social activity change, DPC = dietary pattern change, SPC = sleep pattern change, PIU = problematic Internet use.
( ) = correlations of the same latent variable over a year.

Table 2
Akaike's information criterion (AIC) and the goodness-of-fit statistics for the nested models on the predictive relationships between lifestyle changes and problematic Internet use.

Models	AIC	CFI	RMSEA	SRMR	χ^2	df	Model comparisons χ^2 difference test
PIU–PAC							
Model 1	32,080.09	0.966	0.039	0.036	331.54	156	
Model 2	32,078.76	0.967	0.038	0.035	328.21	155	Model 1 vs. Model 2 $\Delta\chi^2(1) = 3.33$, $p = 0.068$
Model 3[a]	32,073.14	0.968	0.038	0.034	322.59	155	Model 1 vs. Model 3 $\Delta\chi^2(1) = 8.95$, $p = 0.003$[b]
Model 4	32,074.48	0.968	0.038	0.034	321.93	154	Model 3 vs. Model 4 $\Delta\chi^2(1) = 0.66$, $p = 0.416$
PIU–SAC							
Model 1	28,071.50	0.955	0.044	0.042	388.97	156	
Model 2	28,071.83	0.955	0.044	0.041	387.30	155	Model 1 vs. Model 2 $\Delta\chi^2(1) = 01.67$, $p = 0.196$
Model 3[a]	28,059.56	0.958	0.043	0.036	375.02	155	Model 1 vs. Model 3 $\Delta\chi^2(1) = 13.95$, $p < 0.001$[b]
Model 4	28,061.51	0.957	0.044	0.036	374.98	154	Model 3 vs. Model 4 $\Delta\chi^2(1) = 00.05$, $p = 0.832$
PIU–DPC							
Model 1	31567.32	0.959	0.042	0.043	362.04	156	
Model 2	31,568.42	0.959	0.042	0.043	361.14	155	Model 1 vs. Model 2 $\Delta\chi^2(1) = 00.89$, $p = 0.344$
Model 3	31,565.76	0.960	0.042	0.041	358.48	155	Model 1 vs. Model 3 $\Delta\chi^2(1) = 03.56$, $p = 0.059$
Model 4[a]	31,565.63	0.960	0.042	0.041	356.35	154	Model 1 vs. Model 4 $\Delta\chi^2(2) = 05.68$, $p = 0.059$
							Model 2 vs. Model 4 $\Delta\chi^2(1) = 04.79$, $p = 0.029$[b]
PIU–SPC							
Model 1	24,519.92	0.958	0.052	0.045	281.14	92	
Model 2	24,519.79	0.959	0.052	0.043	279.02	91	Model 1 vs. Model 2 $\Delta\chi^2(1) = 02.13$, $p = 0.145$
Model 3[a]	24,517.23	0.959	0.052	0.042	276.45	91	Model 1 vs. Model 3 $\Delta\chi^2(1) = 04.69$, $p = 0.030$[b]
Model 4	24,518.55	0.959	0.052	0.042	275.77	90	Model 3 vs. Model 4 $\Delta\chi^2(1) = 00.68$, $p = 0.411$

[a] The best fit model.
[b] The model is improved if $p < 0.05$.

Table 3
Standardized coefficients in the cross-lagged relationship models of four lifestyle changes and PIU.

	PIU–PAC				PIU–SAC				PIU–DPC				PIU–SPC			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
a	.79***	.78***	.76***	.76***	.65***	.64***	.63***	.63***	.65***	.66***	.64***	.65***	.67***	.66***	.66***	.66***
b	.71***	.70***	.69***	.68***	.65***	.65***	.63***	.63***	.54***	.55***	.52***	.53***	.67***	.66***	.65***	.65***
c	.73***	.74***	.55***	.58***	.65***	.66***	.51***	.51***	.65***	.65***	.58***	.55***	.63***	.64***	.53***	.55***
d	.69***	.57***	.70***	.65***	.67***	.62***	.70***	.69***	.68***	.72***	.69***	.75***	.69***	.63***	.70***	.67***
e			.22**	.19*			.21***	.21***			.11	.14*			.13*	.12
f		.14		.06		.07		.01		−.05		−.08		.08		.05

Note: PAC = physical activity change, SAC = social activity change, DPC = dietary pattern change, SPC = sleep pattern change, PIU = problematic Internet use.
M1 to M4 represents Model1 to Model 4, respectively.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

moderately stable across one year. For the cross-lagged paths, PIU at Time 1 positively predicted PAC at Time 2 ($e = 0.22$, $p < 0.01$), while PAC at Time 1 did not predict PIU at Time 2.

5.4.2. Social activity change and problematic Internet use

For the PIU–SAC model, Model 3 was significantly better than Model 1 ($\Delta\chi^2 = 13.95$, $p < 0.001$), but the model specification of Model 4 was not significantly improved compared with Model 3 ($\Delta\chi^2 = 0.05$, *n.s.*). The AIC value showed that Model 3 was more parsimonious (AIC = 28059.56) than the other models. In Model 3, synchronous correlations between SAC and PIU were moderately positive (Time 1 $a = 0.63$, $p < .001$; Time 2 $b = 0.63$, $p < 0.001$; please refer to Table 3). The auto-regressive coefficients of SAC and PIU were both significant (SAC: $c = 0.51$, PIU: $d = 0.70$, $ps < 0.001$), suggesting that measures of SAC and PIU were moderately stable across one year. Of the possible cross-lagged paths, only PIU at Time 1 positively predicted changes in social activities at Time 2 ($e = 0.21$, $p < 0.001$). Those students presenting more problematic Internet use in their freshman years had cross-year effects on social activities in the following year.

5.4.3. Dietary pattern change and problematic Internet use

For the PIU–DPC model, neither the goodness-of-fit indices of Model 2 nor those of Model 3 were significantly better than those of Model 1, and the fit indices of Model 4 were only marginally better than those of Model 1 ($\Delta\chi^2 = 5.68$, $p = 0.06$, AIC = 31,565.63). A further comparison indicated that Model 4 fit the data better than did Model 2 ($\Delta\chi^2 = 4.79$, $p = 0.03$, AIC = 31,565.63). In Model 4, synchronous correlations between DPC and PIU were moderately positive (Time 1 $a = 0.65$, Time 2 $b = 0.53$, $ps < 0.001$; see Table 3). The auto-regressive coefficients of DPC and PIU were significant (DPC: $c = 0.55$, PIU: $d = 0.75$, $ps < 0.001$), suggesting that DPC and PIU measures were moderately stable across one year. Although Model 4 (denoting a reciprocal relationship) provided the best fit and was the most parsimonious, a reciprocal relationship between DCP and PIU was, surprisingly, not warranted. The cross-year effect from DPC at Time 1 to PIU at Time 2 was not significant ($f = -0.08$, *n.s.*). Only PIU in the freshman year positively predicted changes in dietary pattern in the following year ($e = 0.14$, $p < 0.05$). Therefore, as with the temporal effects between PIU and other lifestyle changes, college students' PIU could lead to cross-year changes in dietary patterns.

5.4.4. Sleep pattern change and problematic Internet use

For the PIU–SPC model, again, similar conclusions could be drawn, based on the same methods described above. Model 3 fitted the data significantly better than Model 1 ($\Delta\chi^2 = 4.69$, $p < 0.05$), meanwhile, when compared with Model 4, Model 1 did not

provide a better fit than Model 3. Therefore, Model 3 was the best fit, with the smallest AIC among the four models (AIC = 24517.23). In Model 3, synchronous correlations between SPC and PIU were moderately high (Time 1 $a = 0.66$, Time 2 $b = 0.65$, $ps < 0.001$; see Table 3). The auto-regressive coefficients of SPC and PIU were significant (SPC: $c = 0.53$; PIU: $d = 0.70$, $ps < 0.001$), suggesting that SPC and PIU measures were moderately stable across time. Of the possible cross-lagged paths, only PIU in the freshman year was positively related to changes in physical activity in the following year ($e = 0.13$, $p < 0.05$). These results showed that changes in sleep pattern at Time 2 could be positively predicted by problematic Internet use at Time 1; the reverse temporal effect was not found to be significant.

6. Discussion and implications

6.1. Relationship between problematic Internet use and lifestyle changes

The present study investigated the temporal relationship of PIU and lifestyle changes among Taiwanese college students using SEM. To ensure the validity and reliability of the measurements of PIU and lifestyle changes, measurement evaluations were conducted first. These evaluations included (1) measurement invariance over time, (2) construct stability over time, and (3) Cronbach's α. The measurement invariance results confirmed that consistent measurement structures existed, with equal loadings, across two time periods. The Model 1 results (for all four lifestyle changes) indicated moderate stabilities for the constructs of PIU and the four types of lifestyle change. Cronbach's α values also suggested high internal consistencies for the scales of PIU and the four lifestyle changes. Overall, measurement evaluation revealed that the measurements were valid, reliable, and stable over time.

Our first research question was whether PIU predicted subsequent changes in sleep, diet, and physical and social activities. From the results of the model comparisons for all four of the lifestyle changes, we found PIU was a prospective predictor of lifestyle changes. High Internet dependence temporally affected unhealthy lifestyles up to one year later. Lifestyle changes measured at two time points (auto-regression effects) could be viewed as long-term habits of sleep, dietary, physical and social activities. When the yearly lifestyle habits as well as the synchronous relationships of PIU and lifestyle changes were controlled, PIU could still predict the subsequent four lifestyle changes. Consistent with this finding, Kim et al. (2010) reported that students with PIU are more likely to exhibit poor eating habits and sleep patterns. Contrast to the research results of Ho and Lee (2001), which suggested students who spent more time on computer games tend to be less physically active and to have low self-perceived social supports, the present study concerned a relevant issue that whether problematic Internet use had negative impact on physical and real social activities of college students. Our findings suggest that the students who have PIU symptoms are also likely to reduce exercise or physical activities, and reduce face-to-face contact with friends and family.

Our second research question involved whether lifestyle changes predicted subsequent PIU. The third question concerned the possible existence of a hybrid between the two unidirectional relationships, in which prior PIU temporally predicts subsequent lifestyle changes while simultaneously prior unhealthy lifestyle also temporally predicts subsequent PIU. Our results failed to support the hypothesis that prior lifestyle changes predominantly predicted PIU; the predictive relationship between PIU and lifestyle changes was not reciprocal. The students who exhibited less/more lifestyle problems did not show lower/higher PIU symptoms in their subsequent college year.

In the present study, the definition of PIU was a lack of control and addictive states (i.e., impulse Internet use, impairment of control, tolerance, and withdrawal symptoms) due to the excessive use of the Internet. Unhealthy lifestyle changes could be the initial step of impairments in daily lives due to Internet use. Many researchers have considered functional impairments (e.g., impairment of social relationships, conceptually close to our lifestyle changes definition) as the criteria for Internet addiction diagnosis. In establishing diagnostic criteria for Internet Addition, most researchers (Ko et al., 2005; Shapira et al., 2003; Young, 1998) have agreed that the mental states associated with PIU results in functional impairment. Thus far, none have investigated the temporal relationship between PIU and lifestyle changes. However, it is possible that lifestyle change is a precursor of the mental/emotional states associated with problematic Internet use. The question of whether less unhealthy lifestyle changes lower the possibility of future PIU symptoms has also arisen. The major contribution of the current study is to provide answers to these questions. According to our results, prior PIU affects subsequent lifestyle changes and lifestyle changes are consequences of PIU. However, prior lifestyle changes do not lead to subsequent PIU symptoms.

6.2. Implications

This study contributes to the literature by providing cross-lagged analyses that examines the predictive relationships between PIU and lifestyle changes from a longitudinal perspective. We found that college students with severe PIU tended to have increased unhealthy lifestyles in the subsequent year and that those with lower PIU were likely to have healthier lifestyles over time. Therefore, maintaining a healthy lifestyle is an important step toward good quality of life. In contrast, unhealthy lifestyles may result in severe damage to life functions; for example, excessive use of the Internet disrupts healthy lifestyles and leads to problems in school and at work (Cao & Su, 2006). Therefore, to promote healthy lifestyles among college students, more emphasis on eliminating PIU is needed. We hope that the findings of the present study will support the need for efforts to tackle the impacts of PIU such that useful prevention and interventions can be enacted. Because higher educations are moving toward Internet-based solutions and entirely reducing Internet use by college students is unrealistic, therefore, the goal for primary prevention should be raising the awareness of the cause and the consequences of PIU among students. We recommend colleges to provide supports in the development and implementation of PIU self-awareness programs to increase students' recognition of the issue.

7. Limitations

One limitation of the present study is that we only analyzed data on students in their freshman and sophomore college years. Future research should consider either a shorter or longer length of time in a longitudinal design because different results may be obtained for data collected over different time intervals. Constructing a cross-lagged model for students across all four undergraduate years would produce a complete picture of the relationship between lifestyle changes and PIU over longer time periods. Moreover, a larger and more representative sample would support efforts to generalize the current findings to all Taiwanese college students.

Second, the questionnaire measuring lifestyle changes and the Internet use could be considered as a measurement for context-specific lifestyle changes. However, in a cross-lagged analysis which aims to study temporal relationships between PIU and lifestyle changes, general questions such as "I reduced face-to-face

contact with others in the last 6 months," may better serve the purpose of the study without controversy.

Third, there are a number of factors that may contribute to PIU and possibly to lifestyle changes, such as neurotic personality (Tsai et al., 2009), loneliness and depression (Ceyhan & Ceyhan, 2008; Morahan-Martin & Schumacher, 2003; Whitty & McLaughlin, 2007), and social anxiety (Caplan, 2006; Scealy, Phillips, & Stevenson, 2002). It is worth considering these factors in the PIU–lifestyle changes models to gain further insights into PIU. In addition, Internet game players have been found to be more easily addicted to the Internet than other types of Internet users (Chou et al., 2005). Temporal relationships between PIU and lifestyle changes may need to be compared for different Internet use types.

Last, beyond the issue addressed in this study, there is also a need to investigate PIU symptoms and the effectiveness of specific intervention in the future. For example, a latent profile analysis might help to determine whether groups with different profiles for PIU symptoms exist. This, in turn, may help to identify subgroups of college students who have particular PIU symptom profile, but are recovered most effectively after intervention.

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