ASSESSING THE FACTORIAL STRUCTURE OF THE INTERNET ADDICTION TEST IN A SAMPLE OF GREEK ADOLESCENTS

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Abstract. Although many studies have documented the psychometric properties of the Internet Addiction Test (IAT) in adults, its factorial structure has not adequately been investigated in adolescents. The aim of this study was to investigate the psychometric properties of the Internet Addiction Test, specifically testing its factorial structure in a sample of adolescents. A modified version of the Greek IAT, adapted for adolescents, was administered to 725 Greek secondary-school students. To determine the factorial structure underlying the questionnaire, both traditional and bifactor modelling approaches were applied to derive the optimal measurement structure of the IAT for adolescents. The bifactor model supported the single and three distinct factors, with stronger support for the unidimensionality of the instrument. The present study supports the stability of the three-factor structure of the Greek IAT from adolescence to adulthood, yet a longitudinal study is warranted to confirm this suggestion.

Keywords: Adolescence, Internet addiction, Young Internet Addiction Test

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Acknowledgments. The authors are grateful to all the educational institutions and people that directly or indirectly participated and collaborated in this study.

INTRODUCTION

The influence of the Internet in everyday life is unquestionable; hence it is not surprising that time spent online is increasing. Young people particularly have embraced the Internet and while most use the Internet without any adverse effects some Internet users show addiction-like behaviours. Adolescents with Internet addiction (IA) are more likely to also engage in other addiction-related behaviours, such as substance abuse, pathological gambling, and excessive video gaming, suggesting that IA may be an important predictor of addictive behaviour in vulnerable youth (Watters, Keefer, Kloosterman, Summerfeldt, & Parker, 2013). Studies of prevalence of Internet addiction in adolescents have generated widely different estimates, with European estimates suggesting a range of 1% to 8% (Durkee et al., 2012; Tsitsika et al., 2014). Although more and more studies are focusing on the specific mechanisms underlying the prevalence, development and maintenance of IA in adolescents, further progress in this area is contingent on having a psychometrically sound assessment tool for IA for adolescents. A notable limitation of previous studies in adolescents in this regard is that they used IA measures that have been developed with adult samples and have not been validated for use with adolescent respondents.

Although there are still no gold standard instruments for assessing problematic Internet use, the most widely used instrument to measure Internet addiction internationally is the Young Internet Addiction Test (IAT, Young, 1998). The IAT was constructed based on the official DSM-IV criteria for pathological gambling disorder (American Psychiatric Association, 2000) as a model for outlining the Internet addiction construct and hence may have a better discriminating ability than other IA measures, such as the Pathological Internet Use scale (Morahan- Martin & Schumacher,

2000) that was developed with a key focus on behavioural problems or the Generalized Problematic Internet Use Scale (Caplan, 2002) that was developed from a cognitive-behavioural perspective.

The IAT consists of 20 questions about Internet use that are answered on a Likert scale. These questions cover a variety of Internet-use behaviours and addiction symptoms, such as preoccupation, withdrawal, failure to control, more use than intended, and functional impairment. The IAT has been validated among adult populations in different languages (Chang & Man Law, 2008; Ferraro, Caci, D'Amico, & Blasi, 2007; Khazaal et al., 2008; Korkeila, Kaarlas, Jääskeläinen, Vahlberg, & Taiminen, 2010; Tsimtsiou, Haidich, Kokkali, Dardavesis, Young, & Arvanitidou, 2014). These validation studies have shown that the IAT has high internal consistency, test–retest reliability and concurrent validity, however evidence about its factor structure has been inconsistent. For example, the Italian version revealed a six-factor solution (Ferraro et al., 2007), the French version suggested a one-factor structure (Khazaal et al., 2008), the Greek and Chinese versions extracted three factors (Chang & Man Law, 2008; Tsimtsiou et al., 2014), whilst the Finnish version provided support for a two-factor model (Korkeila et al., 2010). Specifically, the Greek version (Tsimtsiou et al., 2014), tested in a small sample (N = 140) of medical students, found that Internet addiction symptoms, as measured by the IAT, cluster into three distinct factors, which have been named by the authors: ''Psychological/Emotional Conflict'', ''Time Management'' and ''Neglect Work''. The inconsistent findings about IAT factor structure challenge Young's (1998) original view with respect to the unidimensionality of the instrument, and suggest the need for further studies. Because lack of psychometric invariance can undermine valid test score interpretations, it is important to demonstrate the stability of measurement properties of the IAT in different age groups of respondents, such as adolescents.

Adolescence is a period of rapid psychological maturation and of susceptibility to Internet attraction. Internet addiction (IA) in adolescents has been found to have numerous negative outcomes, including negative impact on identity formation (Kim et al., 2012), cognitive functioning (Park et al., 2011), interpersonal relations (Milani, Osualdella, & Di Blasio, 2009), and self-injurious behaviour (Lam, Peng, Mai, & Jing, 2009). To date the psychometric properties of IAT have only been examined in Chinese adolescents where a three-factor model was found to have the best fit (Lai, Mak, Watanabe, Ang, Pang, & Ho, 2013), and in Canadian adolescents where a dominant global IA factor and two narrow distinct factors were found (Watters et al., 2013). Given the high risk for problematic Internet use in adolescence, systematic validation of instruments specifically adapted for this age group are urgently needed. Although the IAT is one of the most commonly used assessment tools in adolescent IA research, it has not been systematically validated for use with school-aged population – an issue which, if left unresolved, could limit the generalisability of test results and impede substantive progress in the area. The present study sought to address this issue by examining the factor structure of the IAT in a large Greek sample of high-school students.

More specifically, the present study aimed to assess the factorial structure (and examine indirectly the developmental stability) of the Greek IAT in a sample of adolescents (13-18 years). Because the original wording of IAT items targets the adult population, we have slightly revised the wordings of a few items so that the scale may be more suitable for the use of adolescents or even the pre-teen population. The results of this study will contribute to the discussion about the factor structure of IAT. The findings will also allow researchers and clinicians to have a better understanding about the dimensionality of the construct of IAT among adolescents. One way around this issue is to fit a bifactor measurement model, where all items are allowed to load onto a common general factor in addition to any specific symptom domains. Thus, the second goal of the current study was to apply bifactor modelling to adolescents' IAT responses as an alternative strategy for deriving the optimal measurement structure in this population. The bifactor model has only been tested once to investigate the optimal measurement structure of IAT (Watters et al., 2013). It was hypothesised that based on the bifactor model, our results would support the existence of a dominant global IA dimension and replicate the three distinct sub-dimensions of the Greek IAT. A final aim of the study was to provide an overview of the extent of the problems caused by IA in the surveyed sample along with related socio-demographic correlates. Investigating the factorial structure of the IAT to an adolescent sample represents a potentially important step in advancing the field of Internet addiction research and practice in Greece.

METHOD

Participants and procedure

Students from ten secondary public schools from Northern Greece were recruited. From an initial group of 774 participants who took part in the study during the 2016-2017 academic year, 49 had one or more items with missing values and were not included in data analyses. Thus, participants totaled 725 (340 males and 385 females). Their mean age was 14.11 years (*SD* = 1.7; range: 13-18 years). With regards to school environment, 409 (56.4%) students attended Gymnasio (i.e., junior high school), and

316 (43.6%) attended Lykeion (i.e., senior high school), of whom 251 were in general (36.4%) and 65 in vocational senior high school (9%). Participants were recruited via presentation of the aims of the study to teachers, school staff members, parents, and students themselves. They completed the study online. The group of participants was recruited on a voluntary basis, and informed consent was granted.

Measures

The latest IAT (Young, 2011) tested in a sample of young adults includes 20 items, each of which is rated on a six-point Likert scale ranging from 0 = does not apply, 1 = rarely, 2 = occasionally, 3 = frequently, 4 = often, and 5 = always. Young (2011) claims that the scale measures the extent of a person's involvement with the Internet. On the basis of the total score obtained on the test, the individual is placed into one of three categories: Normal internet use (i.e., the person has full control of his/her own usage; score from 0 to 39); experiences frequent problems because of excessive Internet use (from 40 to 69); or has significant problems because of Internet use (from 70 to 100).

In the Greek version of IAT for adolescents, four items were modified with considerations of relevance to the age group. For example, ''email'' in Item 7 was modified into ''email and social media", and ''intimacy with partner'' of Item 3 was modified into ''spending time with friends". In the Chinese version of IAT, these items were also modified with considerations of relevance to adolescents (Lai et al., 2013). Table 1 includes all items and denotes all modified items.

To assess the test's face validity five possible test-takers were asked to tell the researchers what they thought each item was assessing after reading them. The responses showed that the modified Greek version for adolescents appeared to reflect the content of the original test.

In addition to the IAT, and following Tsimtsiou et al.'s (2014) approach, participants were asked to complete a structured questionnaire about their demographic backgrounds, ownership of a computer, weekly Internet use patterns, including social media, online gaming, and also use of uncensored websites.

Statistical analysis

After random division of the complete data set into testing (N = 362) and validation (N = 363) datasets, exploratory factor analysis (EFA) was used to identify an initial factor structure in the testing subsample; the fit of the emergent factor structure was then tested using confirmatory factor analysis (CFA) in the validation subsample. Maximum likelihood method was used to estimate model parameters for both EFA and CFA.

For the EFA, Horn's parallel analysis (Horn, 1965) was used to determine the number of factors. This method compares eigenvalues from factor analysis of the actual data with eigenvalues derived from factor analyses of multiple random datasets resampled from the original data. If any observed eigenvalues from the actual data exceeded the 95th percentile of eigenvalues from 1000 simulated datasets (Glorfeld, 1995), the factor was retained. For the interpretation of factor loadings, we used oblimin rotation, given the likely possibility of correlated factors. Relatively low cutoff criteria for loadings of .30 for item retention were used so not to reject potentially relevant if weak loading items at this preliminary stage.

For the CFA, we examined the fit of the model suggested by the EFA. Multiple fit indices were used to assess different aspects of model fit as follows: Root Mean

Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), and the Bentler Comparative Fit Index (CFI). Model fit was deemed as adequate if RMSEA < .06, SRMR < .08 (Hu & Bentler, 1999) and CFI > .90 (Bentler & Bonett, 1990). The chi-square test of model fit was also performed, with a non-significant *p* value indicating acceptable model fit. However, given that even trivial deviations of the tested model from the perfect model can be significant when sample sizes are large (Brown, 2015), as in the current study, significant *p* vales in the chi-square test were possible. For his reason the other indicators of model fit were used along with chi-square.

All analyses were conducted with the *lavaan* (Rosseel, 2012) package in R (R Core Team, 2017). (The R syntax and the table of correlations needed to reproduce the analysis are available from the authors upon request.)

RESULTS

Exploratory factor analysis

Parallel analysis results are shown in Figure 1, which displays initial eigenvalues from the actual data compared to the eigenvalues from the resampled data. Three observed eigenvalues exceeded the 95th percentile of the corresponding resampled eigenvalues suggesting a three-factor solution. By way of comparison with other methods of identifying number of factors, Kaiser's eigenvalue > 1 criterion suggested three factors, whereas the traditional scree plot suggested one dominant factor. EFA rotated factor loadings are shown in the pattern matrix in Table 1 and suggest factors which we labeled as Dependent/Emotional Use (F1), Interference with Everyday Activities (F2), and Excessive Use /Time Management (F3). Factor loadings were especially weak for Item 4 (How often do you form new friendships with fellow on-line users?), with no loadings above .30 on any factor. Furthermore, Item 4 did not appear to fit as directly with the fundamental conceptual content of the three factors as it did not appear to assess emotionality, daily task interference or the length of time spent online. Moderate correlations between the three factors were found, *r*(F1, F2) = .49, .56, .51 for F1, F2, F3, suggesting a degree of common dimensionality across factors.

[Insert Figure 1 here]

[Insert Table 1 here]

Confirmatory factor analysis

The fit of the three-factor model that emerged from the EFA of the testing sample was assessed in the validation sample (N = 363) using CFA. The two items (Q13, Q19) identified in EFA as having relatively weak loadings (.34 and -.32, respectively) on their respective factors were included in the analysis so that loadings could be computed for further inspection. Item 4, however, was dropped from analysis, due to its poor fit conceptually and statistically (see previous section). CFA was performed on the sample variance-covariance matrix of the 19 items; factor covariances were allowed to vary, and factor variances were fixed to 1. Given some positive skew in several items, the Satorra-Bentler ML estimator was used given its robustness to non-normality. All model fit statistics reported are those computed after the application of the Satorra-Bentler correction.

Three-factor model. Results indicated a significant chi-square for the overall model fit, $\chi^2(149) = 250.09$, $p < .001$. Other model fit indices suggested some evidence of acceptable fit with SRMR = .05, and CFI = .90 and RMSEA = .06, narrowly failing to meet the suggested thresholds of > .90 and < .06 respectively. Standardized loadings are shown in Table 2. They range from .48 to .69, supportive of an internally consistent solution, with high inter-factor correlations observed, r = .78 to .83. Modification indices were inspected for local areas of model strain. However, no obvious theoretically coherent pattern in areas of model misfit could be observed and under these conditions no further refinements are advisable (Brown, 2015).

Coefficient omega, which provides a superior assessment of reliability compared to Cronbach's alpha (Raykov, 2001), was computed and suggested good reliability for Factors 1 (ω = .83), two (ω = .77) and three (ω = .74).

[Insert Table 2 here]

Bifactor model. The emergence of three strongly correlated factors suggests a substantive common factor influence. As such, we explored a bifactor model using the same validation sample. This model is particularly useful for assessing constructs that may have a large unidimensional influence as well as smaller subdomain influences (Brown, 2015). Unlike the correlated-factors and higher-order IAT models utilised in past studies, a bifactor structure can easily accommodate the unique nature of the outcomes items by modelling them as part of the general IA dimension shared among all the IAT items. Moreover, because any remaining systematic co-variation among the items would be captured by their loadings on the narrower group factors, the bifactor approach also makes it possible to estimate the relative sizes of the general and specific symptom components. More specifically, the bifactor model is specified with all factors uncorrelated, and thus assesses the degree to which domain-specific factors directly influence item response above and beyond general factor influences, and therefore helps to evaluate the substantive contribution of domain-specific factors. We also considered a second-order hierarchical model, which also assesses a common factor influence, but hypothesizes that the common factor affects item responses indirectly via its influence on individual domains (Brown, 2015). However, both three-factor and second-order hierarchical models are mathematically equivalent models (with three estimated factor correlations replaced by three estimated second-order factor paths) and thus produced identical model fit. Thus, the fit of the bifactor model was compared with the nested three-factor model, using the chi-square difference test, where $p < .05$ would indicate significantly better fit of the bifactor model. We also computed the Bayesian Information Criterion (BIC), which assesses model fit after applying a penalty for model complexity, with lower values representing a more favourable fit.

A significant chi-square for the overall fit of the bifactor model was observed, $\chi^2(133) = 219.11$, $p < .001$, with other fit indices (SRMR = .045, CFI = .91, RMSEA = .06) generally indicating favorable fit. The chi-square difference test also showed the bifactor model to have a significantly better fit than the correlated three-factor model $\chi^2(16) = 30.89$, $p = .013$. Nevertheless, a smaller BIC value for the three-factor model (19.946) compared to the bifactor model (19.993) favoured the former due to its decreased complexity. As such we followed Reise, Moore, and Haviland (2010) to assess the relative contributions of general and domain-specific factors by examining the standardized loadings of each factor. Table 3 shows that the majority of loadings for the general factor exceeded .45, strongly suggesting a general factor influence.

Table 3 also shows generally lower loadings for the specific factors. In terms of the total item variance explained, the general factor explained 30% and specific factors 10% (4.4%, 2.7%, 2.6%). This indicates that the proportion of total explainable item variance that can be attributed to the general factor, known as the ECV statistic (Reise et al., 2010), is 75%, with specific factors explaining the remaining 25%. For this reason, it was decided that the IAT could be used as indicative of a general factor, so that the cut-off criteria based on a total IAT score can be used.

[Insert Table 3 here]

Classification of adolescent Internet use

Using the proposed cut-off criteria (Young, 1998), based on total IAT scores, results showed 564 (77.8%) participants with IAT score from 0 to 39, suggesting normal Internet use, 150 (20.7%) participants with IAT score from 40 to 69, revealing excessive Internet use, 11 (1.5%) participants with IAT score from 70 to 100, suggesting significant problems because of Internet use. Correlations between IAT scores and weekly internet use, $r = .369$, $p <. 001$, being a video game user, $r = .340$, $p < .001$, weekly social media use, $r = .081$, $p < .05$, and use of uncensored (pornographic, violent, etc.) websites, $r = .371$, $p < .001$, were significant.

In addition, there were significant gender differences on the total IAT score: Male participants scored significantly higher than females, $t(723) = 4.21$, $p < .001$. Males also scored significantly higher than females on Dependent/Emotional Use (F1), $t(723) = 5.21$, $p < .001$, Interference with Everyday Activities (F2), $t(723) = 2.45$, $p < .05$, but no gender differences were found on Excessive Use/Time Management (F3) $t(723) = 2.15$, $p > .05$.

DISCUSSION

Although many studies have reported the psychometric properties of the IAT in young adult populations in various countries, very few studies have established its factorial structure in adolescents. The present study examined the factorial structure of the Greek version of the IAT modified for use in adolescents. This adolescent study showed support for both a single and a three-factor model with stronger support for the unidimensionality of the IAT. The three-factor replication of the Greek IAT indirectly suggests its stability from adolescence to adulthood. This study also expands on prevalence rates of Internet addiction in Greek adolescents and reports correlates with Internet-use parameters, such as, weekly internet use, weekly online gaming, weekly social media use, and use of uncensored (pornographic, violent, etc.) websites.

This adolescent study, using bifactor modeling, indicated that while both a general and a three-factor model (i.e., “Dependent/Emotional Use”, “Interference with Everyday Activities”, and “Excessive Use”) may influence item responses on the IAT, the former may be more influential in dictating item responses. Based on our findings, and in agreement with previous reports of a strong general factor in adults (Chang & Law, 2008; Khazaal et al., 2008; Korkeila et al., 2010), our recommendation is that the IAT scale should be scored unidimensionally in adolescents to provide a single Internet addiction score. However, when there is a need to examine the influence of specific factors (e.g., on outcome variables or for clinical use formulation) the results do suggest that individual subscales can be computed when there is a strong rationale for doing so. Interestingly, the three distinct factors found in the present study consist of very similar (but not identical items) to the ones that comprise the three factors (i.e., Psychological/Emotional Conflict, Time Management, and Neglect Work) found in the Greek validation adult study (Tsimtsiou et al., 2014). This replication indirectly suggests the stability of the three-factor structure of IAT from adolescence to adulthood, yet a well-designed longitudinal study is warranted to confirm this suggestion.

It is possible that the variability reported in the factorial structure of the IAT in different languages could be due to differences in the technical procedures adopted for analysis or due to variability in samples rather than different representations of the construct. Although the current study represents the second application of bifactor analysis in the IAT literature, and there is still a possibility that our results might be sample-specific, we believe this to be a fruitful new direction for the IAT research and encourage future studies to test bifactor solutions of the IAT with both adolescents and adults.

The study also found 1.5% of participants were classed as Internet addicts, which is in line with prevalence rates in other European countries (Durkee et al., 2012; Tsitsika et al., 2014) and is very similar to the one reported by an earlier Greek study (Tsitsika et al., 2009), perhaps indicating an emerging problem in adolescence that warrants further investigation. Furthermore, significant positive correlations were found between scores of the IAT and internet use parameters such as overall time spent online, as well as video game, social media and uncensored website use, in agreement with previous studies (Lai et al., 2013; Watters et al., 2013). As the proposed diagnostic criteria of Internet addiction (Beard & Wolf, 2001) includes the excessive time spent on Internet the significant correlation between IAT and weekly Internet use provides some evidence for the convergent validity of IAT.

We also found that males were at higher risk for Internet addiction than females, which has also been reported in other studies (Anderson, 2001; Chou & Hsiao, 2000;

Jang, Hwang, & Choi, 2008). In the present study, although males obtained a higher total IAT score, there was no difference on the "Excessive Use/Time Management" domain between genders. This may suggest that the higher vulnerability to Internet addiction in males may be associated with a different pattern of symptom manifestation. Future studies should be conducted to examine the effects of gender on the risks of Internet addiction among adolescents. Researchers may use the adapted scale to further develop the knowledge of Internet addiction in adolescents in Greece and refine the assessment of it by improving on this initial validation.

The main limitations of the present study are sampling of participants who contained only secondary school students, the lack of an overall addictive sample as well as lack of additional measures to test the external validity of the scale. The results from our sample may not be generalisable to the entire Greek adolescent population, although the participating schools were of different school bandings, covering students from low to high academic abilities. Clearly, more research is needed with larger and more varied samples to further establish the validity of the instrument. In conclusion, this study has provided additional evidence on the factorial structure of the assessment of Internet addiction in adolescence, which could benefit future research on the life-course risks of Internet addiction.

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Table 1. EFA on testing sample (N = 362): Loadings for a three-factor solution (loadings > .30 highlighted in bold).

Note. * denote the modified items

	Item	F1	F2	F3
Q20	How often do you feel depressed, moody or nervous when you are off-line, which goes away once you are back on-line?	**0.76**	-0.03	0.11
Q19	How often do you choose to spend more time on-line over going out with others?	**0.71**	-0.04	-0.06
Q15*	How often do you feel preoccupied with the Internet when off-line?	**0.61**	0.12	0.04
Q3*	How often do you prefer the excitement of the Internet to spending time with your friends?	**0.52**	0.10	-0.04
Q12	How often do you fear that life without the Internet would be boring, empty, and joyless?	**0.45**	0.08	0.10
Q10	How often do you block out disturbing thoughts about your life with soothing thoughts of the Internet?	**0.38**	0.25	0.01
Q13	How often do you snap, yell, or act annoyed if someone bothers you while you are on-line?	**0.34**	0.21	0.25
Q9	How often do you become defensive or secretive when anyone asks you what you do on-line?	**0.32**	0.12	0.09
Q6*	How often do your grades or school work suffers because of the amount of time you spend on-line?	-0.04	**0.72**	0.05
Q11	How often do you find yourself anticipating when you will go on-line again?	0.26	**0.61**	-0.14
Q2	How often do you neglect household chores to spend more time on-line?	0.07	**0.47**	0.28
Q8	How often does your school performance or extracurricular activities suffer because of the Internet?	0.26	**0.39**	0.06
Q14	How often do you lose sleep due to late-night log-ins?	0.11	**0.38**	0.23
Q7*	How often do you check your email or social media before something else that you need to do	-0.06	**0.38**	0.19
Q17	How often do you try to cut down the amount of time you spend on-line and fail?	0.01	0.03	**0.63**
Q16	How often do you find yourself saying “just a few more minutes” when online?	0.11	-0.05	**0.63**
Q18	How often do you try to hide how long you’ve been on-line?	0.29	-0.02	**0.52**
Q1	How often do you find that you stay on-line longer than you intended?	-0.09	0.33	**0.44**
Q5	How often do others in your life complain to you about the amount of time you spend on-line?	0.00	0.30	**0.41**
Q4	How often do you form new relationships with fellow on-line users?	0.17	0.29	-0.06

Table 2. CFA correlated factor model: Standardised factor loadings (all significant at p < .001)

Factors	Items	Std. Loading
Factor 1	Q20	0.69
	Q19	0.58
	Q15*	0.68
	Q3*	0.58
	Q12	0.58
	Q10	0.58
	Q13	0.62
	Q9	0.66
Factor 2	Q6*	0.63
	Q11	0.62
	Q2	0.68
	Q8	0.64
	Q14	0.60
	Q7*	0.48
Factor 3	Q17	0.50
	Q16	0.67
	Q18	0.63
	Q1	0.59
	Q5	0.61

Factor correlations:

	F2	*F3*
F1	0.79	0.78
F2		0.83

Note. * denote the modified items

Table 3. Bifactor model: Standardised factor loading

Items	General Factor		Specific Factors
Q20	0.58	Factor 1	0.40
Q19	0.47		0.39
Q15*	0.61		0.27
Q3*	0.44		0.46
Q12	0.56		0.15
Q10	0.52		0.26
Q13	0.57		0.23
Q9	0.57		0.32
Q6*	0.53	Factor 2	0.55
Q11	0.66		-0.02
Q2	0.62		0.28
Q8	0.57		0.30
Q14	0.54		0.17
Q7*	0.46		0.11
Q17	0.38	Factor 3	0.46
Q16	0.59		0.35
Q18	0.58		0.22
Q1	0.51		0.29
Q5	0.56		0.19

Note: Loadings for all factors significant at $p < .05$, except for specific factor loadings for Q11 ($p = .74$) and Q7 ($p = .14$)

* denotes the modified items