iSCALE: Unveiling the Digital Addiction Quotient - A Comprehensive 6-Item Measure for Internet Compulsion

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Abstract

The study investigated the psychometric properties of the 14-item Compulsive Internet Use Scale and sought to adapt it to a brief 6-item form (CIUS-6) based on Griffiths' component model of addiction. The study sampled 273 university students with mean age 34.6 (SD = 12.5) of which 68% were female. Assessment of the proposed CIUS-6 confirmed unidimensionality, acceptable reliability and validity at the item and construct levels. Additionally, three latent classes of compulsive internet use, namely 'high risk', 'medium risk' and 'low risk' were identified. A higher risk of compulsive internet use was associated with younger females with low self-control. Further, compulsive internet use was positively correlated with risky online behaviour. The optimal cutpoint of the CIUS-6 was determined to be 12, which gave a prevalence of 19.5% for compulsive internet use. In addition, the criteria of relapse/loss of control and mood modification showed the highest discriminative powers. The study concluded that the CIUS-6 is a psychometrically valid scale and that compulsive internet use is associated with psychological problems and potentially negative outcomes such as risky online behaviour. Further, the 14-item CIUS can be reduced to a format that is based on Griffith's six criteria of addiction, to allow easier comparison to studies examining various forms of social media addiction.

Keywords: Compulsive Internet use Scale; Rasch model; latent profile analysis; psychometric validation; Griffiths components model; risky online behaviour

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Dr Troy Smith is a graduate of the Doctor of Philosophy programme offered by the Institute of Criminology and Public Safety, University of Trinidad and Tobago. He is a scholar with multiple peer-reviewed articles and ongoing international projects focusing on the areas of cybercrime, problematic social media use and the effect of exogenous shocks on crime patterns. He also actively seeks to enhance research within the social sciences through the use of alternative statistical methods where appropriate; for example, the use of Bayesian analysis and Rasch measurement. He has over fourteen years of experience working in the area of national security in various specialty areas within Trinidad and Tobago. He is currently one of the directors of Research Analysis Inquiry and Development, a research non-profit entity focused on producing quality multidisciplinary research within the Caribbean.

Introduction

Compulsive internet use is defined as a pathological preoccupation with the Internet, which can lead to psychological and physical impairment, i.e., it is an impulse control disorder (Dalal & Basu, 2016). Scholars view compulsive internet use as a multifaceted disorder that can take the form of excessive or maladaptive use of social media, online gaming, shopping and pornographic websites. However, they vary in terms of motives and needs affordance (Young et al., 2017). It has been associated with decreased productivity (academic and occupational), relationship problems, financial difficulties, comorbid psychopathologies such as depression, anxiety, and obsessive-compulsive disorder (Billieux et al., 2012; Khazaal et al., 2022). Moreover, studies have shown that compulsive internet use is associated with other forms of addiction, such as substance abuse and gambling (Lin & Tsai, 2016).

The mechanism underlying compulsive internet use is not fully understood, but research suggests that the release of pleasure-inducing brain chemicals such as dopamine and endorphins play a key role (Kuss & Griffiths, 2011). Furthermore, studies have found that individuals with compulsive internet use have alterations in brain structure and function, particularly in regions associated with impulse control, decision-making, and emotional regulation (Kuss & Griffiths, 2011). However, the concept of compulsive internet use is not universally accepted, as some researchers argue that it is not a distinct disorder, but rather a manifestation of underlying psychiatric conditions such as depression, anxiety, and attention deficit/hyperactivity disorder (ADHD) (van Rooij et al., 2011). In addition, a common criticism of the concept has been that the Internet should be considered the medium (or the delivery mechanism) for problematic behaviours, not the object of the addiction per se (Starcevic, 2013). Researchers such as Baggio et al. (2018, 2022) propose that people do not become addicted to the Internet but to one or more types of online activities (e.g., gaming, gambling, cybersex, social networking, or TV series watching).

Two covariates of compulsive internet use which are of interest are self-control and risky online behaviour. Self-control is a key component of addictive behaviour and can influence the development and maintenance of compulsive internet use. Studies have found that individuals with low self-control experience greater difficulty in regulating internet use and maintaining offline activities and relationships (Donkin et al., 2011; Papacharissi, 2010). Researchers have proposed that low self-control increases risk of compulsive internet use by making individuals more vulnerable to the reinforcing effects of the internet as they are intrinsically more focused on the receipt of short-term rewards that the internet provides (Kuss & Griffiths, 2011).

Another growing relationship of interest is between risky online behaviour and compulsive internet use, particularly as risky online behaviour is an antecedent for cybercrime victimization (Gámez-Guadix et al., 2016; Jiang et al., 2018; Toozandehjani et al., 2021). Empirical evidence suggests that compulsive internet use can increase the likelihood of engaging in risky online behaviours by reducing self-control and increasing impulsivity (Kardefelt-Winther, 2014). There is an intrinsic increase in risk since the individual spends

more time online, which leads to greater exposure to harmful content, such as illegal drugs, gambling, child exploitation, online fraud and other forms of cybercrime (Kardefelt-Winther, 2014).

The Compulsive Internet Use Scale

To better understand the nature of this behaviour and its impact on users, researchers have developed various measurement tools to assess the extent of internet use and the manifestation of addiction-like behaviours. One of these scales is the Compulsive Internet Use Scale (CIUS), developed by Meerkerk et al (2003). The CIUS is a measurement tool developed to assess the possibility that a user is experiencing compulsive internet use, which results in problematic, compulsive, and maladaptive online behaviours. The scale assesses the symptoms of compulsive internet use, which Meerkerk et al (2003) identified as the inability to control internet use, preoccupation with being online, agitation when the Internet is inaccessible or limited, perceived changes in mood when online, and conflict with others over the level of internet engagement.

The CIUS has been adapted and psychometrically tested in various cultural contexts and among specific groups with consistently good psychometric properties (Milasauskiene et al., 2021). Nevertheless, there remains a dispute among scholars regarding the factor structure and item inclusion of the CIUS (Milasauskiene et al., 2021). While several scholars have confirmed the CIUS' original 14-item one-factor structure (Lopez-Fernandez et al., 2019) others have proposed a three-factor structure (Alavi et al., 2011; Yong et al., 2017). Further, Lopez-Fernandez et al (2019) and Milasauskiene et al. (2021) have demonstrated the viability of short versions of the scale with 5, 7 and 9 items respectively.

The current study aimed to examine the psychometric properties of the CIUS for the first time in a Caribbean country among a sample of university students. To date, the psychometric properties of the CIUS have not been assessed in the Caribbean cultural context, as research into the compulsive use of the internet has been limited. Further, the study sought to develop a short form of the CIUS, consisting of 6 items, that follows Griffith's (2005) six criteria of addiction, like Bergen's Social Media Addiction Scale (BSMAS; Andreassen et al., 2015). This would enable easier use in a clinical setting and better comparison between compulsive internet use and the related area of problematic social media use.

Methods

Participants

The participants of this study were university students at the University of Trinidad and Tobago who were all over the age of eighteen (18). The Research Ethics Committee granted permission to distribute a self-administered online questionnaire to the students via email. The survey was administered during the first semester of the 2022-2023 academic year. The study captured data from 273 respondents, which comprised of 68% females. Age (M = 34.6, SD = 12.5)

ranged from 18 to 65 years. In addition, 72.3 % were single, 3.1% were co-habiting/common law, 22.3% were married and 2.3% were divorced.

Measures

Demographics

Gender was represented as a dichotomous variable, while age was given as ordinal (18–24, 25–34, 35–44, 45–54, 55–64 & 65 or older). Additionally, marital status was captured as a nominal variable with the four options of single, co-habiting/common-law, married and divorced.

Compulsive internet use

The Compulsive Internet Use Scale (CIUS) (Meerkerk et al., 2009) was used to measure pathological or maladaptive internet use in this study. This scale is made up of fourteen (14) 5-point Likert-type items, which ranged from 'never' = 0 to 'very often' = 4. A higher overall score indicates a stronger case for the user experiencing compulsive internet use, i.e., a greater manifestation of maladaptive behaviours.

Validation Variables

Given that the external criteria of self-control and risky online behaviour have been widely identified as being associated with problematic use of online services (and addiction in general) the study selected these factors for the validation of the LPA classification. The Brief Self-Control Scale (BSCS) (Tangney et al., 2004) was used to measure general trait self-control in this study. A higher score indicates a stronger case for the individual having more self-control. The Cronbach α and McDonald's ω for the BSCS were found to be 0.870 and 0.874 respectively. The construct of risky online behaviour was measured using the Risky Online Behaviour Scale (ROBS) (Smith et al., 2023). The scale consists of four factors (communicating with strangers and risky sexual behaviour, social networking and self-disclosure, handling emails, and accessing unsolicited content). A higher score indicates a stronger case for the individual engaging in higher levels of risky online behaviour. In this study, Cronbach α was 0.758 and McDonald's ω was 0.792 for the ROBS.

Data analyses

Several analyses were performed using Jamovi version 2.3 to provide a description of the respondents and to analyse the reliability and structural validity of the CIUS. As a preliminary step, the Barlett test for sphericity and the Kaiser-Meyer-Olkin (KMO) test were performed to assess the suitability of the data for factor analysis (suitability given as $p < 0.05$) and sampling adequacy respectively (KMO index > 0.6). Psychometric testing was done using both Classical Test Theory (CTT) and the Rasch model to enable assessment of the CIUS at both the construct and item levels. Machine learning techniques including Latent Profile Analysis and classification were also performed to identify the relative importance of the scale items and to create a more precise compulsive internet use risk classification mechanism than the simple use of a cut-off point.

The CIUS' internal consistency was assessed on the four metrics of Cronbach's α, McDonald's ω, composite reliability (CR) and average variance extracted (AVE). It is generally accepted that a Cronbach α of 0.6 - 0.7 indicates an acceptable level of reliability, and 0.8 or greater is a very good level (Ursachi et al., 2015). The CR is considered a less biased estimate of reliability than Cronbach's α, while AVE indicates the average percentage of variance explained by the scale items used to measure the latent construct. A value of 0.6 and above is considered a good value for CR while a score of 0.5 may be considered acceptable for the AVE (Alarcón & Sánchez, 2015; Awang, 2015). Together the CR and AVE are thought to best assess the convergent validity of the measurement tool (Fornell-Larcker, 1981).
To confirm the one-factor model of the CIUS Confirmatory Factor Analysis (CFA) using maximum likelihood estimation (MLE) estimation was implemented. Absolute fit, incremental fit and parsimonious fit were all considered in the evaluation of the suitability of the one-factor model. A p-value of the goodness of fit index (GFI) higher than 0.9, root mean square error of approximation (RMSEA) less than 0.05 (with *p*-value > 0.05) and a standardized root mean square residual (SRMR) less than 0.08 were used for the absolute fit (Barrett, 2007; Byrne, 2013). 0.90 were used for incremental fit (Bentler, 1990). While χ^2/df values less than 2.0 were used as the measure for parsimonious fit (Tabachnick & Fidell, 2007).

In terms of Rasch analyses, a Rasch rating scale model was used to report the item difficulty (how easy it is to agree with an attitudinal item), and to examine item validity, categorical functioning in the response scale, and item and person reliability. Item difficulty was presented on a Wright map that plots the items in an instrument according to their order of difficulty on the right using a linear scale (standardized). On the left, a bar chart shows the distribution of respondents in relation to the latent trait. Item validity was tested by evaluating the size of randomness or distortion in the measurement system (fit) (Boone et al., 2014). The measures of 'fit' used were information weighted fit statistic (infit) mean square (MnSq), and outlier sensitive fit statistic (outfit) MnSq with a recommended range between 0.5 and 1.5 suggesting a good fit (Jafari et al., 2012).

Once the above steps were completed the model and items were assessed for contribution to the model, redundancy, categorical functioning, and fit, then matched with Griffiths' six-criteria to narrow the tool from 14 to 6 items. After, the validation process using CTT and IRT was repeated for the brief CIUS (CIUS-6) measurement tool. At this point, gender differences were assessed using Multi-Group Confirmatory Factor Analysis (M-CFA) and Differential item functioning (DIF). M-CFA and DIF were performed to assess measurement invariance across gender to validate related comparisons in the examination of the CIUS-6 at the construct and item level respectively.

Latent profile analysis (LPA) was conducted on the CIUS-6 data to identify the latent subpopulations based on the varying levels of compulsive/maladaptive behaviour of participants. Models with 2–4 classes were estimated based on the Akaike information criterion (AIC), Bayesian information criterion (BIC), approximate weight of evidence (AWE), (CAIC), sample size adjusted BIC (SABIC) and entropy. The validity of the results of the LPA

identification of the classes was assessed by comparing them to external criteria (self-control and risky online behaviour) and demographics (gender and age).

The determination of an optimal empirical cutpoint was achieved by using sensitivity analysis with a focus on Youden's index, F1 score and a balance between sensitivity and specificity (Thiele & Hirschfeld, 2021). Similar, to the works of Smith and Short (2022) and Bányai et al., (2017) on social media addiction, the 'at-risk' group obtained from latent profile analysis was used as a 'pseudo gold standard' to separate cases from non-cases for the sensitivity analysis.

Results

14-item CIUS Scale

Preliminary Analysis

The mean overall CIUS score for the participants was found to be 19.5 (SD = 9.84). The appropriateness of the data for factor analysis was also assessed using Bartlett's test of sphericity (correlations within data) and Kaiser-Meyer-Olkin (KMO; assess the level of common variance among scale items) test for sampling adequacy. The dataset was found to be suitable for use with data reduction techniques (e.g., Confirmatory Factor Analysis) as the null hypothesis of the variables being orthogonal was rejected: $\chi 2\ (91) = 1240$, $p < .001$. Further, all KMO measures of sample adequacy were greater than 0.5 (Hair et al., 2009; Kaiser, 1974).

Rasch Analysis

For the 14-item CIUS the person reliability was found to be 0.879, suggesting that the scale may be able to classify respondents into 2 to 3 categories in relation to the construct. The mean absolute value of the centered Q_3 statistic (MADaQ3) was 0.13 (the closer this value is to zero, the better the scale aligns with a one-factor model). To confirm one-dimensionality, the Martin-Löf Likelihood-Ratio-Test was performed, which returned a significant value ($\chi 2=57.6$ df=38 p=.021) suggesting that the scale is not unidimensional. Checks of the MnSq Infit and Outfit values show that all items except Item 3 (Infit = -1.706 and Outfit = 1.788) fall within the range of 0.5 - 1.5. This suggests that Item 3 represents a deviation from one-dimensionality in the data, not in the measures, i.e., the unidimensional additive measures present a distorted picture of the data.

An examination of the Wright map (Figure 1) shows one gap in the continuity of difficulty between Item 3 and Item 10 of the scale. Further, it is highlighting that there are four cases where question difficulty overlaps. Table 1 captures the items and the associated questions where levels are at comparable item difficulty.

Figure 1

Wright Map of the Compulsive Internet Use Scale (14-item)

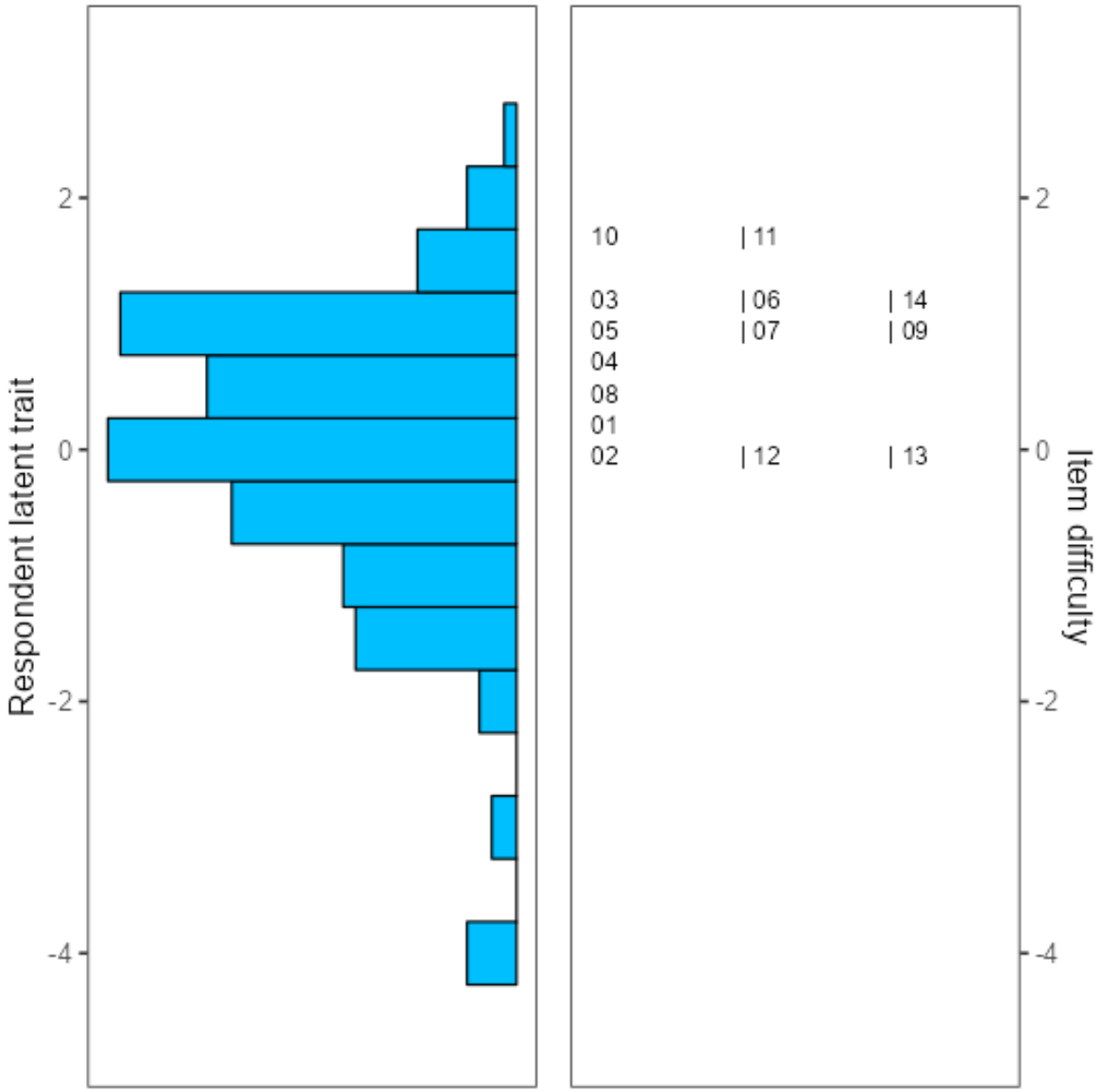


Table 1

Comparison Chart for the Selection of Suitable Items for the CIUS-6

Identifier	Griffiths Criteria	Factor Loading	Residual Correlation	Item with equivalent difficulty	Infit/Outfit Outside of Threshold	Included in All versions of the CIUS
Item 1	Tolerance	0.633	Item 2			X
Item 2	Tolerance	0.849		Item 12, Item 13		
Item 3	Conflict	0.406	Item 3, Item 11	Item 6, Item 14	X	
Item 4	Conflict	0.724	Item 8, Item 9			
Item 5	Relapse/Loss of Control	0.437		Item 7, Item 9		X
Item 6	Salience	0.775	Item 7, Item 12, Item 13	Item 3, item 14		
Item 7	Salience	0.743	Item 13	Item 5, Item 9		
Item 8	Conflict	0.797	Item 9			
Item 9	Relapse/Loss of Control	0.700		Item 5, Item 7		
Item 10	Conflict	0.540		Item 11		
Item 11	Conflict	0.624	Item 12	Item 10		X
Item 12	Mood Modification	0.703		Item 2, Item 13		X
Item 13	Mood Modification	0.845	Item 13	Item 2, Item 12		
Item 14	Withdrawal	0.524		Item 3, Item 6		

Factor Structure and Internal Consistency

In this study, Cronbach α was 0.735 and McDonald's ω was 0.746 for the CIUS-6. The reliability/internal consistency of the PTTUS was found to be Cronbach's α = .0.896; McDonald's ω = 0.901. Further, convergent validity was confirmed with a CR of .901 and an AVE of 0.402. A one-factor model of the CIUS with six dimensions (salience, tolerance, mood modification, relapse, withdrawal and conflict) was tested with CFA. The analysis provided the following results for measures of absolute fit to the data: $\chi^2(77) = 474$ ($p < .001$), RMSEA =.178 ($p < .001$), GFI = 0.993. Metrics for incremental fit were CFI = 0.669 and TLI = 0.609. Standardized factor loadings ranged from 0.406 to 0.849, with Item 3 being the only item with a factor loading less than .5. Results showed the $\chi^2/df = 6.16$, which was above the threshold value of 5.

Six-item Brief CIUS Scale

The selection of items for the 6-item scale sought to balance the reliability of the item in its measurement of the construct, reduce overlap in item difficulty, and align the scale with the widely accepted framework for addiction presented by Griffiths (2005). As such, several factors were considered, which are captured in Table 1.

Table 2 shows the selected items in the 6-item version of the Compulsive Internet Use Scale (CIUS-6) and compares it to other versions of the scale.

Preliminary

CIUS-6 mean score was 8.25 (S.D. = 4.16) with the respondent range being 0 to 19.

Rasch Analysis

The one-dimensionality of the scale was assessed using the Martin-Löf Likelihood-Ratio-Test, which return a value that led to the rejection of the null hypothesis ($\chi^2 = 134$ df = 127 $p = 0.327$) indicating that the item set is unidimensional. Further, the mean absolute value of centred Q_3 statistic (MADaQ3 = 0.0712) suggests a better fit to one-dimensionality than the 14-item version of the CIUS, i.e., the MADaQ3 of the 6-item version is closer to zero. For the 6-item CIUS, the person separation reliability was found to be 0.717, which corresponds to the scale being suitable to classify respondents into at least two levels in relation to the manifestation of the construct (compulsive internet use). The Infit and Outfit values of all six items fall within the acceptable 0.5 - 1.5 suggesting that all items are productive for the measurement of the construct.

Table 2

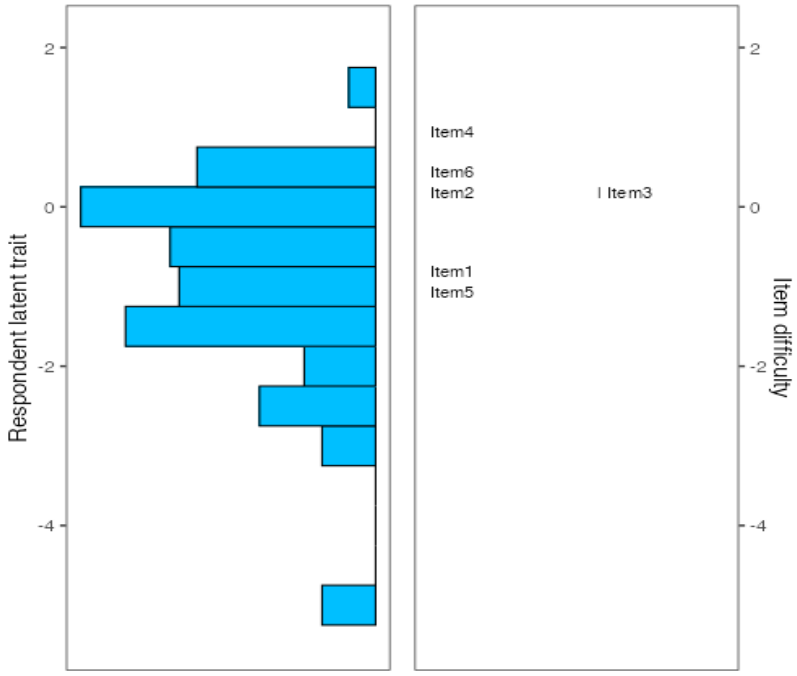
Items with High Discriminative Power and Alignment with Griffiths Criteria of Addiction (CIUS-6 in Comparison with Items of other Short CIUS Versions)

CIUS 14-item	Item Label	CIUS-9	CIUS-8	CIUS-5	CIUS-6
1	Do you find it difficult to stop using the Internet when you are online?	X	X	X	X
2	Do you continue to use the Internet despite your intention to stop?				
3	Do others (e.g., partner, children, and parents) say you should use the Internet less?	X		X	
4	Do you prefer to use the Internet instead of spending time with others (e.g., partner, children, and parents)?	X	X		
5	Are you short of sleep because of the Internet?	X	X	X	X
6	Do you think about the Internet, even when not online?				
7	Do you look forward to your next Internet session?	X	X		X
8	Do you think you should use the Internet less often?				
9	Have you unsuccessfully tried to spend less time on the Internet?	X	X		
10	Do you rush through your (home) work in order to go on the Internet?				
11	Do you neglect your daily obligations (work, school, or family life) because you prefer to go on the Internet?	X	X	X	X
12	Do you go on the Internet when you are feeling down?	X	X	X	X
13	Do you use the Internet to escape from your sorrows or get relief from negative feelings?				
14	Do you feel restless, frustrated, or irritated when you cannot use the Internet?	X	X		X

The relative difficulty of questions and the distribution of the latent trait were visualized using Rasch analysis with a Wright map (see Figure 2). Except for Item 2 and Item 3, each item measures a different level of the latent trait. A considerable gap was identified between Item 1 and Item 2, which suggests that for a more precise measure of the latent trait, an item or items of relevant difficulty can be added at this point. However, the items do cover a suitable range of the various levels of the trait, particularly at the medium to high levels.

Figure 2

Wright Map of the Compulsive Internet Use Scale (6-item)



Factor Structure and Internal Consistency

In this study, Cronbach α was 0.735 and McDonald's ω was 0.746 for the CIUS-6. The reliability/internal consistency of the PTTUS was found to be (Cronbach's α = .0.735; McDonald's ω = 0.746). The CR and AVE for the CIUS-6 were determined to be 0.746 and 0.336 respectively. Although the AVE is less than 0.5, Fornell and Larcker (1981) suggest that once the CR is greater than 0.6, the convergent reliability of the construct is still adequate (Hair et al., 2009). A one-factor model of the CIUS with six dimensions (salience, tolerance, mood modification, relapse, withdrawal and conflict) was tested with CFA. The analysis provided the following results for measures of absolute fit to the data: $\chi^2(9) = 9.08$ ($p = 0.430$), RMSEA =.007 ($p = .706$), GFI = 0.993. Metrics for incremental fit were CFI = 0.998 and TLI = 0.997. Standardized factor loadings ranged from 0.458 to 0.773. The $\chi^2/df = 1.01$, and this was below the threshold value.

Equivalence test (Gender Differences)

To confirm that meaningful and valid comparisons can be made across gender using the CIUS-6, measurement invariance was assessed using Multi-group Confirmatory Factor Analysis (M-CFA). When the configural invariance was examined, the model achieved an acceptable fit with GFI = 0.967 indicating the overall factor structure holds similarly for both sexes. Metric and Scalar invariances were also found to be acceptable with the model fit score remaining at 0.967; i.e., there was no notable decrease in fit when factor loadings or intercept equivalence were constrained. Therefore, a valid comparison of variance, covariance and factor means across genders is possible.

To assess the existence of gender differences at the construct level, the two one-sided t-tests (TOST) of the equivalence method was used. The results of the TOST yielded a p-value of 0.435, which suggests that at the construct level males and females are equivalent in their likelihood of experiencing compulsive internet use. Differential Item Functioning (DIF) was used to assess differences at the individual item level. An examination the results showed that gender differences were found in Item 1 ($p < .001$), Item 2 ($p = .016$), Item 3 ($p < .001$) and Item 5 ($p = .004$)

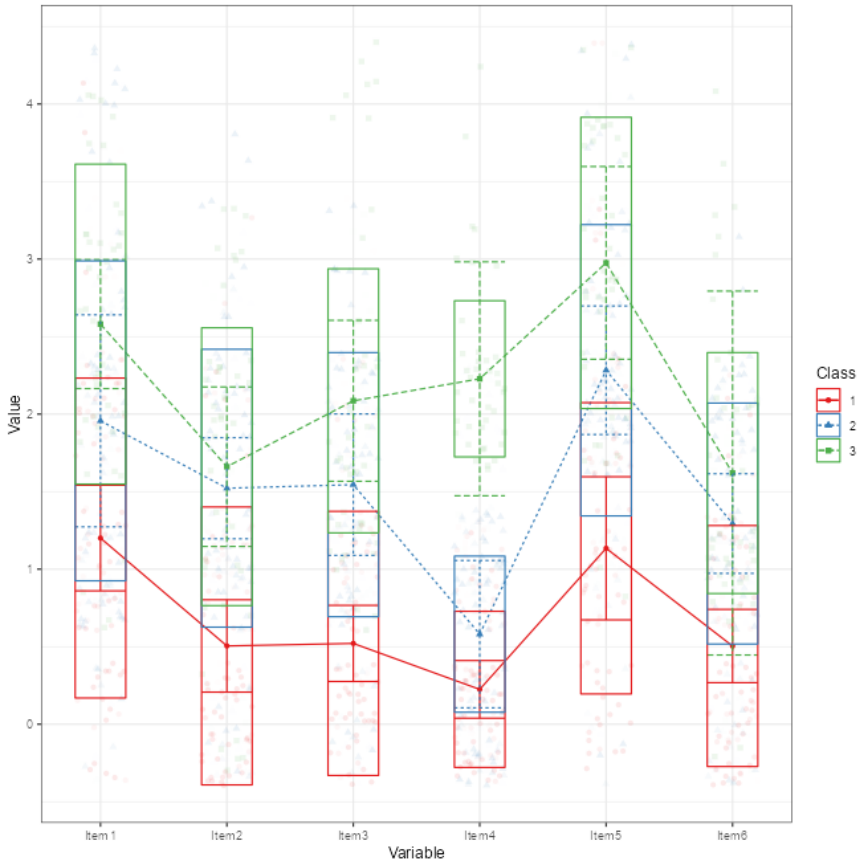
Latent Profile Analysis

LPA was performed on the six items of the CIUS-6, and based on the metrics obtained, the three-class solution was selected as the best-fitting model. While the AIC decreased (slightly) and the BIC increased between models 3 and 4, the 3-class model was also supported by a larger entropy and significant BLRT. The 3-class was also supported by the person reliability of 0.717 obtained from the Rasch analysis, which assesses whether the scale discriminates the sample into enough levels for the needed purpose. The literature suggests that a score more than 0.5 and closer to 0.8 or close will discriminate the sample into 2-3 levels (Bond et al., 2020).

The resulting three classes were grouped as follows: Class 1 (low risk users), Class 2 (medium risk users) and Class 3 (high risk users). The ‘low risk’ class represented 35.4% of users, the ‘medium risk’ class represented the most users at 40.7%, while the ‘high risk’ group consisted of 24.1% of users. The profiles of participants grouped into the three classes are presented in Figure 3. It was observed that within the ‘high-risk’ group, that Item 4 and Item 5 showed elevated levels compared to other dimensions.

Figure 3

Latent Profile for the 3-class Solution of CIUS-6 (N = 273)



Note: Class 3 ('high risk', green), Class 2 ('medium risk, blue), Class 1 ('low risk', red)

The results of the ANOVAs and the accompanying ad hoc pairwise tests (Table 3) suggested that all indicators were influential in the clustering (class assignment) process. This was evidenced by the scores of the criteria in the 'high risk' group being consistently higher than those in the 'medium risk' group and similarly 'medium risk' higher than 'low risk'. Additionally, the results verify that Item 4 had the largest effect size which was followed by Item 5. This suggests that the main signs of a high-risk user are Conflict (preference for online activity over offline communication) and Relapse/Loss Control (loss of sleep to engage in the use of the Internet).

Table 3

Comparison of the Two Latent Classes: Testing Equality for Latent Class Predictors (N= 173)

Addiction Criteria	Class 1 [Low risk] (n = 35.2%)	Class 2 [Medium risk] (n = 40.7%)	Class 3 [High risk] (n = 24.1%)	One-Way ANOVA	Pairwise Comparison of classes	Effect size (ε^2)
Item 1	1.19 (0.95)	1.92 (1.19)	2.59 (0.88)	<.001	3> 2 > 1	.23
Item 2	0.47 (0.78)	1.50 (0.95)	1.67 (0.98)	<.001	3, 2 > 1	.28
Item 3	0.47 (0.57)	1.55 (0.89)	2.08 (1.09)	<.001	3, 2 > 1	.39
Item 4	0.25 (0.43)	0.53 (0.50)	2.26 (0.55)	<.001	3> 2 > 1	.66
Item 5	0.95 (0.85)	2.41 (0.88)	2.95 (0.89)	<.001	3> 2 > 1	.49
Item 6	0.44 (0.59)	1.32 (0.77)	1.62 (0.96)	<.001	3, 2 > 1	.31
Overall	3.77 (1.84)	9.32 (1.95)	13.2 (2.35)	<.001	3> 2 > 1	.81

Note: For each variable the class mean is provided with the standard deviation in brackets

Validation and Characterization

The results of ANOVAs and pairwise comparisons between classes regarding demographics and covariates are presented in Table 4. There was a significant difference in age among classes, with members of the 'high-risk' class (class 3) having a significantly higher probability of being younger than persons in the other classes. The psychological factor of self-control was also found to be significantly different between classes. Persons with low self-control are more likely to be categorized in class 3 than class 2 or 1, i.e., as self-control decreases, the risk of compulsive internet use increases. Similar findings were found for risky online behaviour as it increased as the risk went from low (Class 1) to high (Class 3).

Table 4

Associations among Latent Classes, Demographic Characteristics, Covariates and Cybercrime Victimization

Variable	**Class 1 [low risk] (n = 35.2%)**	**Class 2 [medium risk] (n = 40.7%)**	**Class 3 [high risk] (n = 24.1%)**	**Test**	**Pairwise Comparison of classes**	**Effect size (ε^2)**
Demographics						
Sex (Female %, Male %)	58.1%,41.9%	73.2%,26.8%	74.2%, 25.8%	χ^2 (2) = 3.18, *p* = .204		--
Age	38.6 (12.0)	34.4 (13.9)	29.4 (7.89)	χ^2 (2) = 10.1, *p* = .006	1 > 2 > 3	0.079
Self-control	27.6 (9.31)	32.9 (8.45)	36.8 (5.55)	χ^2 (2) = 34.7, *p* < .001	3 > 2 > 1	0.252
Risky Online Behaviour	4.32 (5.26)	5.2 (4.67)	6.09 (3.69)	χ^2 (2) = 14.2, p < .001	3 > 2 > 1	0.088

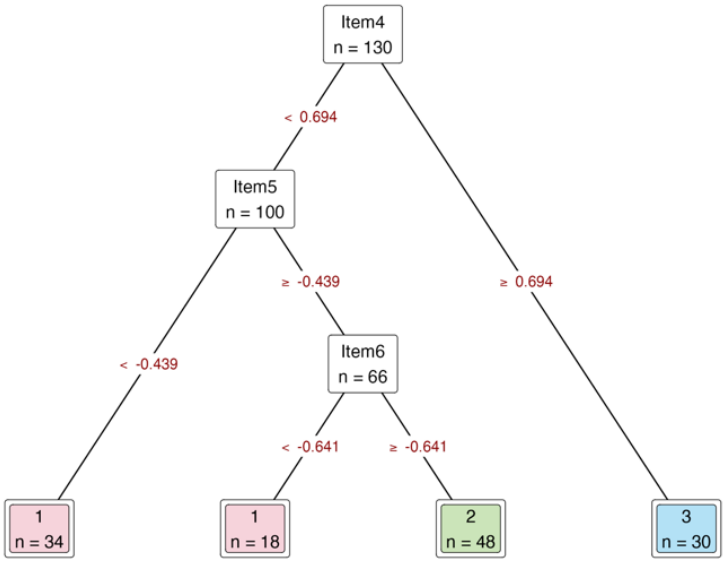
*Greater proportion of females to males in Classes 3 and 2

Prediction of Compulsive Internet Use Using Machine Learning (Decision Tree)

The decision tree classifier had an accuracy of 87.5%. However, accuracy alone is insufficient in the assessment of performance, especially if the data is imbalanced as it may provide misleading results. In such a case, especially if precision and recall are both important, F1 Score and Matthews's correlation coefficient (MCC) are more suitable. For the decision tree algorithms, the F1 score ranged was 0.871 and the MCC was 0.907. Further, the most important item used in classification was Item 4 (Relapse/loss of Control) followed by Item 5 (Mood Modification). The decision tree model also shines in the ease of representation of the process of class selection as is shown in Figure 4.

Figure 4

Decision Tree for the Classification of Internet Users into the LPA Derived Classes of Compulsive Internet Use



Identification of an Empirical Cut-Off Score for the PTTU Using ROC-AUC

From the analysis, a cut-off score of 12 was suggested as the ideal threshold above which persons would be classified as 'high-risk' of compulsive internet use. The Youden index was 0.773, the Area Under Curve (AUC) was 0.953 and the F1-Score was 0.815. With scores for all the combined metrics being greater than 0.7, this cutpoint was taken as a very good model for the classification of cases of compulsive internet use. Further, the specificity was 92.68% and the sensitivity was 84.62% giving an overall accuracy of 90.7%.

Discussion

The present study achieved several objectives which were the psychometric testing of the CIUS 14-item measurement tool, the development and validation of a six-item version of the CIUS, the identification of latent risk profiles of compulsive internet use, the determination of an empirical cut-off point for the CIUS-6, and the development of machine learning classification models. The results show that the 14-item CIUS has a poor global overall model fit and may be better represented as a multifactor scale. In comparison, the CIUS-6 was found to have good global model fit, reliability and validity with the ability to separate users into three latent classes.

Findings of both the CTT and Rasch model approaches suggest that the 14-item CIUS is not unidimensional as indicated by the poor model fit using CFA and the significant Martin-Löf

Likelihood-Ratio-Test similar to previous studies (Lopez-Fernandez et al., 2019; Milasauskiene et al., 2021). Further, the Rasch analysis showed that Item 3 (measuring the criteria of Conflict) did not fit within a unidimensional structure and as such would provide a distorted picture of the data. However, the model had good internal consistency and acceptable convergent validity, which was consistent with previous studies (Downing et al., 2014). The Wright Map showed that several Items had the same level of difficulty and as such if they assessed the same criteria of addiction may be redundant as they would not add to the scale's ability to separate levels of compulsive internet use.

A review of the items of the 14-item CIUS after classifying each item into one of Griffiths' (2009) criteria of addition, checking R^2 values, Infit/Outfit and level of item difficulty was performed to determine the six items of the CIUS-6. Further, a review of the literature suggested that Item 9 had difficulties related to its interpretation due to its negative formulation and as such were removed (Khazaal et al., 2011). The CIUS-6 was found to match well in its selection of the most discriminating items/criteria to previous studies (Khazaal et al., 2022). The items selected were Item 1, Item 5, Item 7, Item 11, Item 12 and Item 14 (see Table 7). The study found that the CIUS-6 had adequate internal consistency and convergence, though lower than the original scale. Unlike the 14-item CIUS the CIUS-6 was found to be unidimensional using both CTT and Rasch analysis. The Rasch analysis showed that all items of the scale were explained and interpreted well by the unidimensional model and that there was only one case of possible overlap in item difficulty. The Wright Map showed a limitation in the scale's ability to measure compulsive internet use across the entire continuum. However, there were clear levels that could potentially separate into three classes as supported by the person reliability score of 0.717.

The LPA identified three levels of internet use based on the manifestation of maladaptive behaviours. The three levels or classes were high risk (24.1%), medium risk (40.7%) and low risk (35.4%) with the high-risk class being the smallest group. While all items significantly contributed to classification into the three classes Item 4 (Relapse/loss of Control) and Item 5 (Mood Modification) were found to have the largest effect suggesting these were the most discriminating. Gender was not found to be a determinant of the class of compulsive use. While compulsive internet use risk was found to decrease with increasing age, which is like multiple forms of online addiction including social media addiction (Smith & Short, 2022). To validate the LPA classes and test criterion validity, the participant's level of self-control and risky online behaviour were measured. According to the literature, lower levels of self-control and higher levels of risky online behaviour are associated with Compulsive internet use (de Alarcón et al., 2019; Griffiths, 2013; Kuss & Griffths, 2011; Ma, 2011; Wu & Tsai, 2012). This was supported by the findings of the study suggesting a mechanism of impulsivity and preference for quick rewards, which may be exacerbated by continuous and translate into risky online behaviours. The optimal cut-off point was determined to be 12 when optimizing the metrics of F1-Score and MCC. Using the identified cut-off score, the prevalence of Compulsive internet use was identified as 19.5%.

Given that the M-CFA confirmed that valid comparisons could be made across genders gender differences were assessed at the item and construct levels. In this sample mainly composed of young Trinidadian participants, no significant relationship was found between CIUS-6 scores and gender. Studies have had mixed results regarding the relationship between compulsive internet use and gender, although generally males were found to be more addicted to the Internet than females (Khazaal et al., 2022). At the item level, significant differences were found primarily for Item 1, Item 2, Item 3 and Item 5. Similarly, when the difference in levels of endorsement was assessed, females were found to endorse Item 2, Item 3, while males endorsed Item 4 more than males.

Given the disproportionality of importance (see Table 10) of each criterion in predicting compulsive internet use, and identification of at-risk persons, I propose that a simple cut-off point may not best identify addictive behaviour. Instead, a decision tree process may be more accurate. This shows that this type of machine learning approach can potentially be a useful tool to consistently classify persons into risk levels. This does not reduce the need for clinical diagnosis as the final step, but provides a relatively quick and robust method with acceptable accuracy for initial screening. The classification algorithm also confirmed that Item 4 (Relapse/Loss of Control) and Item 5 (Mood Modification) are the parameters with the highest discrimination. Therefore, this indicates that they have a high ability to give more information on the latent trait, which allows for greater differentiation of people in relation to the latent trait. The recognition of 'relapse/loss of control' as a core criterion in the identification of maladaptive behaviours has been rather consistent especially among social media addiction studies (Kuss & Griffiths, 2017; Smith & Short, 2022). Mood modification has only been found to be within the top two parameters in relation to discriminating power in limited studies (Smith, 2022). The importance of mood modification suggests that escapism and needs affordance may play an important role in compulsive internet use.

The study should be interpreted in the context of its limitations. The results depended on self-reported cross-sectional data and as such causality could not be established. Further, no psychosocial outcomes were used to test the convergent and divergent validity of the scale. The measures were also presented in the same order for all participants which may have led to ordering effects.

Conclusions

Reliable and validated tools will allow better and more consistent identification of maladaptive behaviours online. However, these tools must consider the importance of brevity in ensuring or increasing the likelihood of high respondent participation. The results of the study suggest that a

6-item version of the CIUS can be used to assess compulsive internet use. The CIUS-6 has the potential to be a useful tool for researchers and clinicians who are interested in studying or treating compulsive internet use. In addition, it allows for a comparison between the phenomenon of compulsive internet use and social media addictions, which can add to current knowledge on their relationship to each other and the possible existence of a similar underlying mechanism of addiction. Further, this research adds to the extant literature and scholarship in the field as it adds to the validity of the concept of compulsive internet use, its existence in the Caribbean and the measurement tool in a different sample and context. It also adds greater depth to the psychometric analysis of the compulsive internet use measurement tool by combining CTT and the Rasch model in the analysis.

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